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Spatial-temporal metrics to assess collective behavior in team sports

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Spatial-temporal metrics to assess collective behavior in team sports

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Editorial: Spatial-temporal metrics to assess collective behavior in team sports

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tactical behavior, decision-making, performance analysis, sport dynamics, complexity

Editorial on the Research Topic
Spatial-temporal metrics to assess collective behavior in team sports

The analysis of collective behavior in team sports has advanced through the integration of spatiotemporal, technical, cognitive, and computational approaches that aim to describe how teams organize, interact, and adapt under dynamic conditions. The articles compiled in this Research Topic provide a comprehensive overview of these perspectives, spanning different sports and levels of expertise. By combining observational, modeling, and experimental methods, this collection highlights the potential of spatial-temporal metrics to bridge theoretical understanding and applied practice, strengthening the connection between scientific evidence and performance optimization.

Studies focusing on technical–tactical variables aimed to identify which performance indicators most strongly predict success across different team sports. These works quantified the contribution of efficiency in specific phases of play, such as attack and counterattack in beach volleyball (da Costa et al.), or the structure and flow of ball possessions in elite football (Maneiro et al.). Similarly, the investigation of tactical dynamics in Guardiola's teams (Pueyo et al.) revealed how match context influences collective organization. These studies collectively emphasize how match outcomes are determined by the quality and coordination of technical execution within specific tactical phases, reinforcing the value of data-driven indicators for assessing team effectiveness.

A second group of contributions explored the spatial–temporal coordination that underpins collective performance. Using positional and tracking-based analyses, these studies examined how inter-player distances, team dispersion, and synchronization evolve across game phases. Experimental research in 3 × 3 basketball (Ichikawa et al.) demonstrated that explicit tactical cues enhance spacing and offensive coordination, while comparative analyses in youth football (Liang et al.) showed that spatial pressure and interpersonal distance differentiate tactical maturity between cultures. Together, these works confirm that spatial-temporal organization—how teams occupy, share, and adjust space—serves as a core determinant of collective adaptability and effectiveness.

Several studies advanced the use of computational and data-driven methods to model and predict collective behavior. The review by Sotudeh synthesized the methodological foundations for automated formation detection in football, emphasizing the transition from static to dynamic representations of team structure. Complementarily, machine learning applications in the FIFA Women's World Cup 2023 (Iván-Baragaño et al.) and Qatar 2022 (Song et al.) predicted shooting and match outcomes using a range of spatial-temporal and technical indicators. These works share a common goal: to transform large-scale tracking and event data into interpretable models that support tactical decision-making and performance prediction in real competition.

Another dimension addressed concerns the perceptual and cognitive mechanisms underlying team coordination and skilled performance. Habekost et al. proposed a comprehensive model describing the perception–action cycle in elite soccer, integrating attention, anticipation, and feedback processes. Similarly, Piras empirically examined gaze behavior during basketball three-point shots, showing how experts modulate fixation and saccadic control to optimize information use under time constraints. These studies converge in recognizing that perceptual attunement and cognitive control are critical components of collective dynamics, linking visual information processing with decision-making efficiency.

Finally, other contributions analyzed how contextual and structural variables condition collective organization and performance. Lee and Kim examined the impact of functional classification and team composition in wheelchair basketball, revealing the importance of balanced line-ups for optimizing play efficiency. Comparative analyses of match location and cultural background (Pueyo et al.; Liang et al.) further demonstrated that environmental and situational contexts shape how teams coordinate space and adapt strategies. These findings highlight that collective behavior is not only the result of internal team dynamics but also a reflection of structural, environmental, and cultural influences that frame performance in real settings.

Overall, the contributions within this Research Topic illustrate the growing maturity and diversification of research on collective behavior in team sports. Across different disciplines, these studies demonstrate that spatial-temporal metrics, technical–tactical indicators, perceptual–cognitive mechanisms, and computational modeling converge toward a shared goal: explaining how coordination, adaptation, and decision-making emerge from complex interactions among players and their environments. However, this body of work also exposes persistent limitations. Despite methodological advances, there is still a need for standardized metrics and cross-sport validation frameworks that allow comparison and replication across contexts. The ecological validity of many experimental or data-driven designs remains challenging, as does the integration of physical, tactical, and cognitive dimensions into unified models. Moreover, the translation of large-scale tracking data into accessible tools for coaches and practitioners continues to be limited by technological and interpretative barriers. Addressing these gaps is essential to consolidate a coherent, evidence-based understanding of collective behavior.

Future research should move toward the integration of multimodal data sources—including positional, inertial, physiological, and perceptual information—to capture the full spectrum of interactions that define team performance. Combining these datasets with advanced analytical techniques such as machine learning, network theory, and non-linear modeling will enable the development of predictive frameworks that reflect the dynamic and adaptive nature of sport. At the applied level, spatial-temporal metrics hold enormous potential to transform training design and tactical preparation, providing coaches with objective indicators of team cohesion, spacing efficiency, and decision-making speed. Embedding these analyses within the daily training process could enhance players' situational awareness, collective synchronization, and perceptual–cognitive expertise, bridging the gap between scientific knowledge and professional practice.

Author contributions

AG-d-A: Methodology, Resources, Supervision, Writing – original draft. YC: Writing – review & editing. BG: Writing – review & editing. TL: Writing – review & editing.

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The timing of vision in basketball three-point shots

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The aim of the present study was to explore the relationship between gaze behaviour, motor responses and the direction of visual attention when different levels of basketball players were engaged in a basketball three-point shot. Twelve near-experts and 12 amateur basketball players, wearing an eye tracker and an inertial sensor, performed 20 shots on a basketball field, receiving the ball from a teammate, who then acted as the opponent. The trial sequence was subdivided into catching, aiming and ball flight phases. The analysis demonstrated that near-experts exhibited longer fixation durations and saccades of lower amplitude and peak velocity than amateurs. The gaze behaviour showed that all players utilized fixations during the last part of the catching phase, during most of the aiming phase, and during the final part of the ball flight phase. The greatest number of saccades was exhibited between the aiming and the ball flight phases, when the ball was released by the players. Saccades were oriented toward the teammate during the catching phase. Instead, during the aiming and ball flight phases, saccade orientations were not polarized toward a specific visual cue. In conclusion, vision plays a critical role in every aspect of the three-point shot in basketball, from catching the ball, to aiming preparation, and shot execution. It is a key factor in decision-making, spatial awareness, and overall performance in team sports.

KEYWORDS

motor control, attention, perception-action, expertise, eye tracking, microsaccades

Introduction

Basketball is a dynamic and invasion sport, with quick movements and rapid decisions, influenced by visual skills, that involves the vestibular and somatosensory systems in focalizing the target. One of the fundamental skills of this team's sport is the three-point shot, taken from beyond the three-point arc, which is a semicircle located 6.75 meters away from the basket in the FIBA rules. Teams often rely on proficient shooters to score points efficiently from long range. This has revolutionized the sport and contributed to the evolution of offensive schemes, with teams placing emphasis on perimeter shooting and spacing to maximize scoring opportunities (Lidor et al., 2022). In recent seasons, the three-point shot increased in popularity, suggesting that teams were increasingly pursuing offensive strategies aimed at three-point field goals with respect to the two-point shot (Romanowich et al., 2007; Gou and Zhang, 2022). This type of shot adds an extra strategic dimension to the game, as it rewards players who have developed long-range shooting accuracy and can extend defences, creating more space for their teammates to operate closer to the basket (Okazaki et al., 2015; Lidor et al., 2022).

Specific skills that impact shooting performance have been identified, such as anthropometric parameters of the player, shooting technique (height and velocity of ball release, angle of ball flight trajectory, distance from the basket), postural stability and fatigue (Okazaki et al., 2015). Nevertheless, to all these variables, another one that contributes to a better understanding of basketball shooting accuracy is the visual attention (Sirnik et al., 2022). The role of visual attention in the three-point shot in basketball is fundamental and multifaceted, impacting both the shooter and the defenders. Before attempting a three-point shot, a player needs to accurately locate the position of the hoop. Vision helps in focusing on the target and aligning the shot accordingly, playing a crucial role in assessing the distance from the hoop and deciding whether to take the shot, pass the ball or drive to the basket. Peripheral vision helps in making the right decision and recognizing teammates for possible passing, opposing, and positioning (Ryu et al., 2015; Ryu et al., 2013). During the execution of the shot, the shooter relies on visual feedback to ensure proper shooting form. This includes monitoring the trajectory of the ball, the alignment of the shooting arm, and the point of release. Both shooters and defenders need to recognize when a three-point shot opportunity arises. This requires rapid visual processing to assess the situation and react accordingly. In summary, vision plays a critical role in every aspect of the three-point shot in basketball, from catching the ball to shot preparation and execution. It is a key factor in decision-making, spatial awareness, and overall performance on the court (Vickers et al., 2019; Klostermann et al., 2018).

Most of the gaze behaviour studies in sports agree that experts look longer at relevant areas than their lower-level counterparts (for a review, see Mann et al., 2007; Zhang et al., 2022). Fewer fixations of longer durations are necessary to allow detailed parameterization for the required shooting movements. This is in accordance with other authors who deemed this period of fixation to be essential for programming the movement direction, force, and velocity, as well as limb coordination and timing (Timmis et al., 2023). Regardless of the type of eye movements, much attention has been dedicated to fixations, investigated as quiet eye, defined as a fixation or tracking gaze that is located on a specific object or location in the environment (for more information, see Vickers, 2021). Nevertheless, it has been found that our eyes are never stationary, even during fixations, because a kind of micro-movements, called microsaccades, continuously upset the gaze position (Martinez-Conde et al., 2013; Gu et al., 2024). These movements occur when athletes attempt to maintain steady fixation on a single point during a sports sequence (Piras et al., 2015). More recently, the interest in the role of microsaccades and other small saccades during fixation has increased, especially their role during action-perception tasks and the links with visuospatial attention (for a review, see Piras and Raffi, 2023).

During a basketball three-point shot, Vickers et al. (2019) demonstrated that experts tended to spend more time fixating on the centre of the hoop during arm flexion rather than arm extension or during ball release. Moreover, during arm flexion, the participants fixated on the hoop for the first time for a long duration, and this first fixation was initiated during the latter part of the arm preparation phase. As suggested by the authors, during the preparation phase, participants could have utilized the peripheral vision to catch the critical information (e.g., the position of the hoop). This reinforces the visual attention shift, in which central vision is used during the early part of fixations to identify cues, whereas peripheral information is used later in the fixation to select a target for the next saccade (Ryu et al., 2015). Therefore, we can hypothesize that experts, during the phase in which they receive the ball from the teammate, fixate on the player or on the ball, then shift their attention, with microsaccades or small saccades, toward the centre of the hoop just before the releasing of the ball. Bearing in mind the relationship between gaze behaviour, motor responses and the direction of visual attention, the current research investigated the role of gaze behaviour when different levels of basketball players were engaged in basketball three-point shots.

Methods

Participants

Twelve male near-experts and 12 male amateur basketball players volunteered to participate. Near-experts, with a mean age of 22 years old, played at the Serie B level (Italy championship); amateurs, with a mean age of 21 years old, played at the Serie D level (Italy championship) (see Table 1). Based on the sample size of the other studies (Piras et al., 2024; Vickers et al., 2019; de Oliveira et al., 2007; de Oliveira et al., 2006) and an effect size f of 0.35, G*Power (version 3.1.9.2) predicted that a total sample size of 24 would give appropriate power ($1 - \beta$ error probability 0.90) to detect a significant difference at alpha level of 0.05. All players had normal or corrected-to-normal vision. After receiving oral and written information concerning the study protocol, all players signed the informed consent to participate in the study. The study was approved by the Bioethics Committee of our University.

Apparatus

EyeLink II (SR Research), the video-based eye-tracking system, were used to record eye movements binocularly. The device consists of two miniature cameras mounted on a leather-padded headband. Pupil tracking is performed at 500 samples/s, with a gaze resolution of <0.005° and noise limited to <0.01°. The eye tracker was calibrated at the beginning of the experiment and after every 10 shots. Then, data validation and drift correction were performed by applying a corrective offset to the raw eye position data. Calibration and validation of the system were repeated every time a possible measurement error occurred due to participant movement. The accuracy of eye position was checked after every shot, and if necessary, a drift correction was performed. Practice, calibration, validation and data collection took about 20–30 min per participant.

In order to collect the exact time participants made each movement phase, one inertial sensor (Cometa Systems, Italy) was placed on the dorsal face of the right hand. Inertial sensors were synchronized with the external camera of the EyeLink II system to have correspondence between eyes, ball, and body movement data.

Gaze behaviour data

Gaze behaviour consisted of fixations, saccades and microsaccades. Fixations were defined as the time the eyes remained stationary (within 1° of visual angle) for a minimum of 100 ms (Piras et al., 2014) and identified with the software Eyelink Data Viewer, that allows displaying, filtering, and presenting the results. Microsaccades were defined as micro-movements with <1° of visual angle, with a peak velocity smaller than 100°/sec, and with the same peak velocity versus amplitude curve as large saccades (Zuber et al., 1968). All eye movements that exceed 1° of visual angle and with a peak velocity

TABLE 1 Athletes characteristics.

	Near-experts (12)	Amateurs (12)	*p*-value	Cohen's *d*
Age (years)	21.58 ± 4.12	20.50 ± 1.31	0.401	0.35
Weight (kg)	88.50 ± 9.73	78.17 ± 7.07	0.005*	1.27
Height (cm)	192.42 ± 7.12	183.33 ± 7.16	0.007*	1.22
Body Mass Index (kg/m^2)	23.83 ± 1.12	23.23 ± 1.21	0.221	0.51
Practice in basketball (years)	14.25 ± 5.15	13.92 ± 2.35	0.841	0.08
Training sessions (number/week)	7.25 ± 1.91	3.83 ± 0.72	0.000*	1.44
Training sessions (hours/week)	14.42 ± 3.12	7.75 ± 1.36	0.000*	2.40
Expertise level (2021–22)	B	D	\	\
Foot laterality	Right	Right	\	\
Hand laterality	Right	Right	\	\

*Significant different at $p < 0.05$.

>100°/s were identified as saccades. Microsaccades and saccades were considered if they occurred simultaneously in both eyes during at least 3 data samples (6 ms), and identified using the algorithms of Engbert and Kliegl (2003). Saccades and microsaccades rate, amplitude, duration, and peak velocity were calculated for each participant during each shot. Data were excluded 200 ms before and after each blink as well as when the pupil was still partially occluded (Piras et al., 2021b).

Procedure

After a warm-up, a pre-test was performed without the eye tracker, followed by fitting the eye tracker and taking 3–5 practice trials until comfortable. Shots were taken from behind the three-point arc, which is a semicircle located 6.75 meters away from the hoop, on a regular basketball court used in competition. Placed right to the basketball hoop, wearing the Eye tracker and the inertial sensor, participants made 20 three-point shots interspersed by 5 min of rest after 10 shots. During each shot, participants received the ball from the teammate, who then acted as the opponent. The opponent had to actively challenge the participant, using an outstretched hand that was visible in the participant's visual field during the trials. Participants were instructed to step forward to receive the ball and shoot, using the high-style shooting technique (Oudejans et al., 2002), as quickly as possible from behind the three-point line. Athletes were instructed and encouraged by their coach to do their best in each shot as if they were in a real match league.

Statistical analysis

The length of the three-point sequence used for analysis was initially selected. The sequence started when the ball left the hands of the passer and ended when the ball reached the hoop. The sequence was subdivided into three epochs: catching the ball, aiming the hoop, and the ball flight. The catching phase began with the first frame of the video showing the ball leaving the hands of the passer and ended with the frame prior to the ball first contacting the hands of the player. The aiming phase began with the first frame showing the ball first contacting the hands of the player and ended with the frame showing the ball leaving the hands of the player. Then, the ball flight phase was started, which ended with the frame showing the ball passed or did not throw the hoop.

Response accuracy, the percentage of trials in which player's response was correct or incorrect, was determined. It was analysed with repeated measure ANOVA, in which expertise (near-experts, amateurs) was the between-subjects factor, and response accuracy (correct, incorrect) was the within-subjects factor.

The phases of the movement were analysed with repeated measure ANOVA, in which expertise (near-experts, amateurs) was the between-subjects factor, phases of the movement (catching, aiming, ball flying) and response accuracy (correct, incorrect) were the within-subjects factors.

Repeated measure ANOVA was performed to analyse fixation numbers and durations. Expertise (near-experts, amateurs) was the between-subjects factor, phases of the movement (catching, aiming, ball flying) and response accuracy (correct, incorrect) the within-subjects factors.

Repeated measure ANOVA was performed to analyse saccade and microsaccade rate, amplitude, duration, and peak velocity. Expertise (near-experts, amateurs) was the between-subjects factor, phases of the movement (catching, aiming, ball flying) and response accuracy (correct, incorrect) the within-subjects factors.

The two-dimensional distribution of all saccade and microsaccade orientations was calculated based on expertise (near-experts, amateurs) and phases of the movement (catching, aiming, ball flying). The Watson-Williams test for homogeneity of means (Oriana® 4.0) was performed. The null hypothesis was that the orientations of saccades and microsaccades between expertise and phases of movement have similar continuous distribution at the 5% significance level.

Finally, we also calculated the time course of the saccade rates (N°/s) for the entire duration of the trial and subdivided into phases: catching, aiming, and ball flight. Rates were computed for each basketball player and subdivided into near-experts and amateurs using a moving time window of 200 ms. The shaded area around each curve represents the standard error of the mean.

All statistical analysis was done with SPSS, version 22.0 (Chicago, IL, USA). Effect sizes were calculated as the mean difference standardized by the between-subject standard deviation and interpreted according to the following thresholds: trivial, <0.20; small,

≥0.20 < 0.50; moderate, ≥0.50 < 0.80; large, ≥0.80 (Cohen, 1988). Partial eta squared (η_p^2) was used during multiple comparisons. Statistical significance was set at $p < 0.05$. *Post hoc* testing was corrected using the Bonferroni procedure.

Results

All players made more incorrect (mean 11.75 ± 2.4; 59%) than correct (mean 8.25 ± 2.4; 41%) three-point shot ($F_{1,22} = 12.6$; $p = 0.002$; $\eta_p^2 = 0.36$). No significant differences were observed for expertise ($p = 0.41$; $\eta_p^2 = 0.03$).

Analysis of the phases of movement showed significant differences between phases ($F_{2,44} = 492.2$; $p < 0.001$; $\eta_p^2 = 0.96$), in which all players spent more time on ball flight phases and less time during catching (see Figure 1). No significant differences were detected for expertise or response accuracy ($p > 0.05$).

Fixation durations showed significant differences for expertise ($F_{1,22} = 5.8$; $p = 0.024$; $\eta_p^2 = 0.21$), between phases ($F_{2,44} = 20.5$; $p < 0.001$; $\eta_p^2 = 0.48$) and also for the interaction between expertise and phases ($F_{1,22} = 3.7$; $p = 0.042$; $\eta_p^2 = 0.16$). Post-hoc analysis showed that near-experts made longer fixation durations than amateurs, and it was more evident during aiming and ball flight (see Figure 2). No significant differences were observed for response accuracy ($p > 0.05$).

The number of fixations exhibited significant differences for phases, with the highest value displayed during ball flight and the lowest during aiming. No significant differences were observed for expertise, nor for response accuracy ($p > 0.05$).

The Engbert and Kliegl (2003) algorithm to identify saccades and microsaccades reported only saccades >1 degree of visual angle and faster than 100 degrees/sec. Indeed, we did not find microsaccades as they are defined by the literature (Martinez-Conde et al., 2009).

Analysis on saccade rates showed significant differences for expertise ($F_{1,22} = 4.9$; $p = 0.044$; $\eta_p^2 = 0.11$), between phases ($F_{2,44} = 29.1$; $p < 0.001$; $\eta_p^2 = 0.57$), and for their interaction ($F_{2,44} = 3.2$; $p = 0.046$; $\eta_p^2 = 0.10$). Near-experts made fewer saccades than amateurs, and this was particularly evident during catching the ball. All players exhibited the greatest saccade rates during ball flight and the lowest during aiming. No significant differences were observed for response accuracy ($p > 0.05$).

Saccade amplitudes showed significant differences for expertise ($F_{1,22} = 20.4$; $p < 0.001$; $\eta_p^2 = 0.48$) and between phases ($F_{2,44} = 6.5$; $p = 0.003$; $\eta_p^2 = 0.24$), but not for their interaction ($p > 0.05$). Near-experts made saccades of lower amplitude in comparison to amateurs, and this happened during all phases (see Figure 3A). All players exhibited the greatest saccade amplitude during ball flight and the lowest during catching. No significant differences were observed for response accuracy ($p > 0.05$).

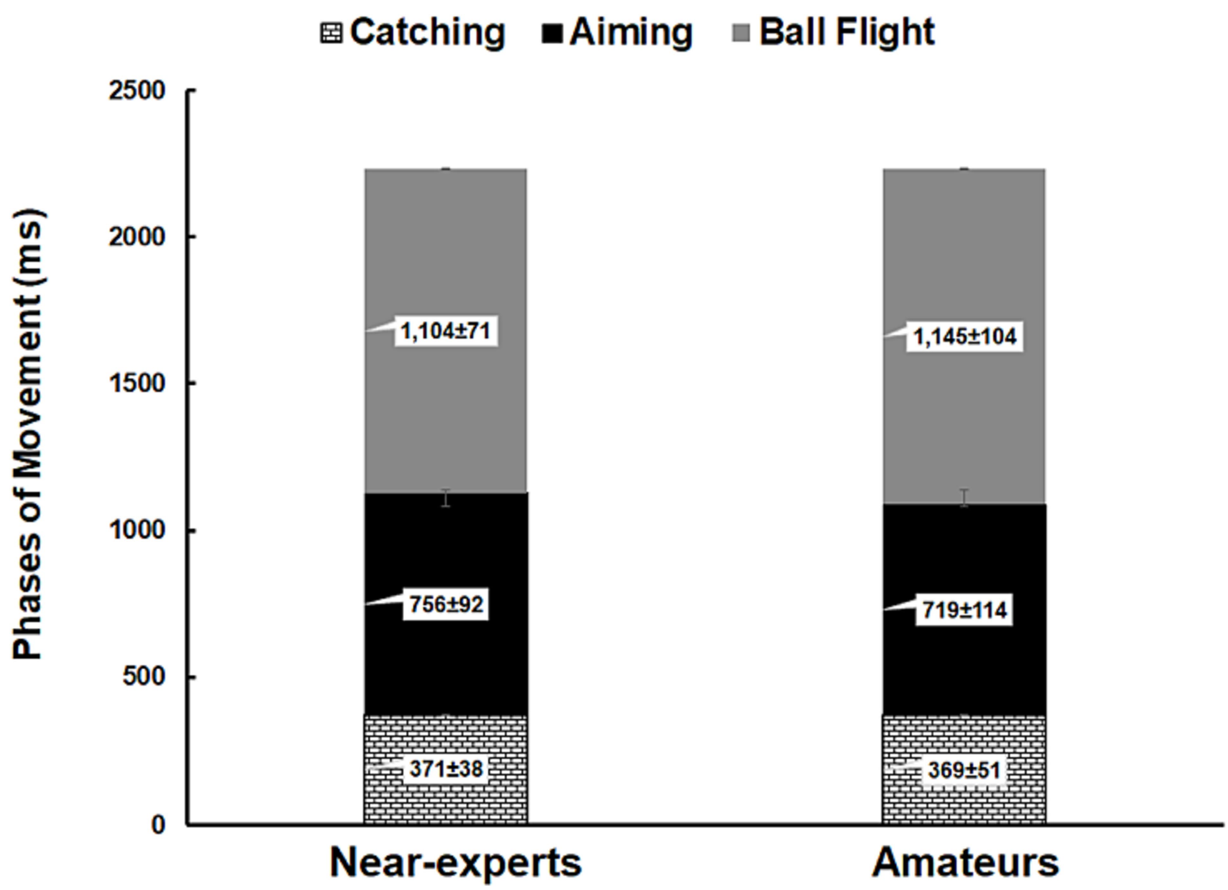

FIGURE 1
Histograms represent the phases of movement (mean ± SD) subdivided into catching (white squares), aiming (black) and ball flight (grey) in both near-experts and amateur basketball players.

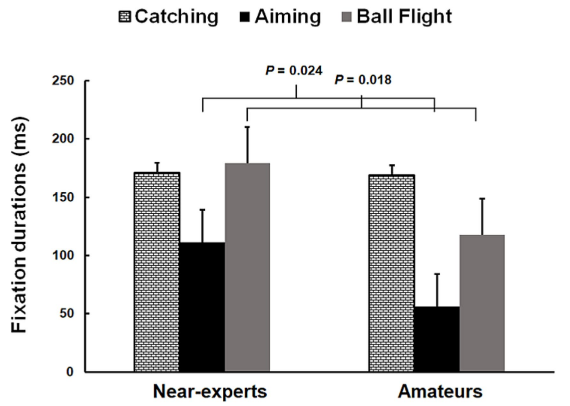

FIGURE 2
Histograms represent values (mean ± SD) of fixation durations (msec) in catching (white squares), aiming (black) and ball flight (grey) between near-experts and amateur basketball players. The horizontal bands represent multiple comparisons at $p < 0.05$.

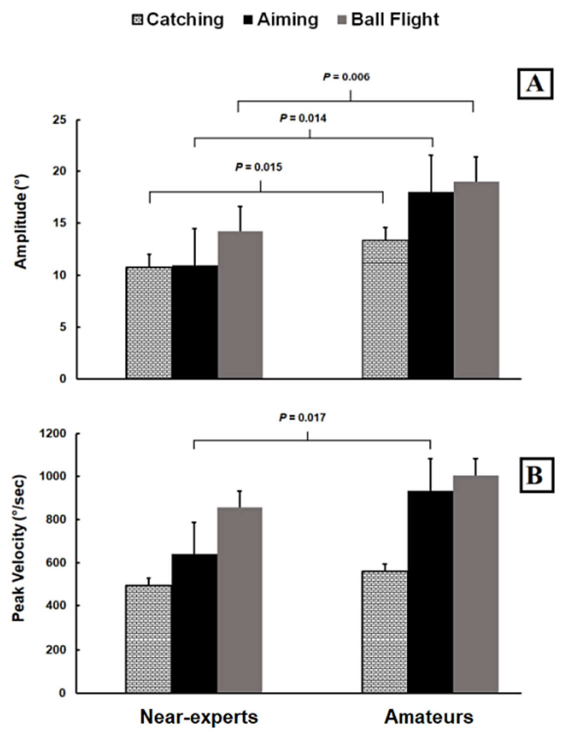

FIGURE 3
Histograms represent values (mean ± SD) of saccade amplitude **(A)** and peak velocity **(B)** in catching (white squares), aiming (black) and ball flight (grey) between near-experts and amateur basketball players. The horizontal bands represent multiple comparisons at $p < 0.05$.

Saccade peak velocities showed significant differences for expertise ($F_{1,22} = 5.3$; $p = 0.031$; $\eta_p^2 = 0.19$) and between phases ($F_{2,44} = 20.8$; $p < 0.001$; $\eta_p^2 = 0.48$), but not for their interaction ($p > 0.05$). Near-experts made saccades of lower peak velocity in comparison to amateurs, and this was more evident during the aiming phase (see Figure 3B). All players exhibited the greatest peak velocity during ball flight and the lowest during catching. No significant differences were observed for response accuracy ($p > 0.05$). No significant differences were observed for saccade durations ($p > 0.05$).

The time course of saccade onset showed a different trend during phases (Figure 4). The greatest values related to the onset of the saccades were observed during the end of the aiming phase and the start of the ball flight phase, at the moment in which the ball was leaving the players' hands toward the basket. The absence of the saccade onset between the catching and aiming phases highlighted the need for the players to maintain stable fixation on the target just before to start the shooting movement.

Saccades orientation showed no significant differences between near-experts and amateurs across movement phases ($p < 0.05$). As shown in Figure 5, while catching the ball, saccades showed a main vector directed to the upper-right of the players' visual field. Meanwhile, the direction of the main vector was inaccurate during the other two phases, showing a greater standard deviation (the ring dimension outside the polar plot, Figure 5), which means that the saccade orientations were not polarized toward a specific direction.

Discussion

The aim of the current research was to investigate the role of gaze behaviour when different levels of basketball players were engaged in basketball three-point shots. This is the first study that has tried to record saccades and microsaccade characteristics during a far-aiming task in a constrained approach, in which athletes were engaged in shooting action against a defender who tried to stop the attack. We did not find microsaccades as they are defined by the literature, which are eye movements inside 1° of visual angle and with a peak velocity lower than 100°/sec. Our data revealed that, in the absence of a foveal target to fixate on and due to the fast sporting sequence, our athletes did not make microsaccades, opting for eye movements of greater amplitude and peak velocity, supporting the suggestion that microsaccades necessitate the presence of a "*target to anchor to*" (Otero-Millan et al., 2008). The absence of a fixation target, or when it is larger than the fovea area, has an effect on the microsaccades, decreasing the rates and increasing the amplitudes (McCamy et al., 2013; Otero-Millan et al., 2019). This is possible because the change of the fixation area through phases forced athletes to move their eyes at great retinal eccentricities. Probably, during a far-aiming task, the athletes' visual search strategy shows more fixations of shorter duration with respect to near or interceptive tasks. This extensive number of perceptual information sources, located disparately across a large field area, constrain the athletes to employ more frequent fixations than in the micro-state contexts (Williams and Davids, 1998). More recently, in soccer goalkeepers, Piras et al. (2021a) found that during penalties kicked from 11 meters, goalkeepers used a visual search strategy with more fixations and consequently greater saccade rates in comparison to penalties kicked from 6 meters, where they exhibited fewer fixations and higher microsaccade rates. In this article, we can only speculate it, even because the soccer goalkeepers performed an interceptive timing task, where the gaze fixates and/or tracks an object moving toward them that must be controlled (receiving the ball). In our study, gaze strategy has been investigated in an aiming task (throwing a ball), in which the gaze fixates on a critical target location(s) before an object is aimed away from the

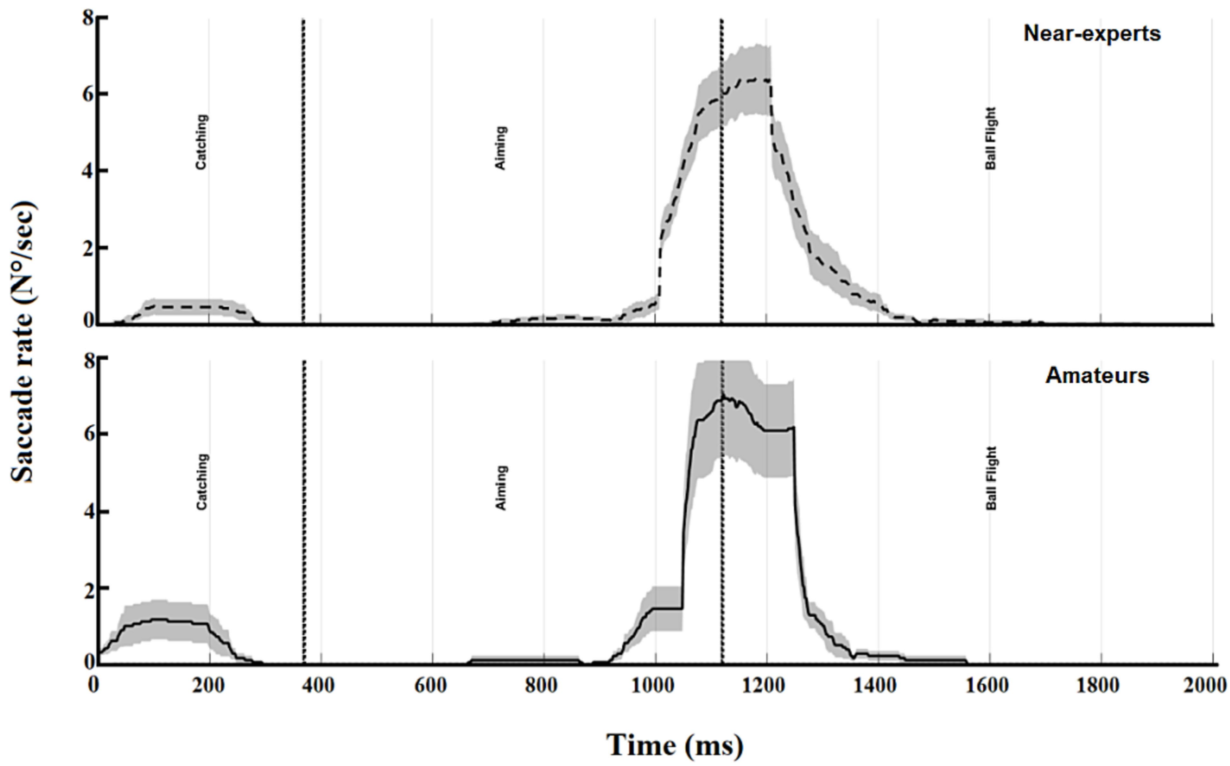

FIGURE 4
The time course of the saccades rate (N°/sec) was calculated for the entire duration of the trial and subdivided into phases: catching, aiming, and ball flight. Rates were computed for each basketball player and subdivided into near-experts (upper panel, dashed line) and amateurs (lower panel, solid line) using a moving time window of 200 ms. The shaded area around each curve represents the standard error of the mean.

body. In the previous studies that have investigated the role of microsaccades in sports, a fixation target was always present; the fixation point in table tennis (Piras et al., 2015; Piras et al., 2019) and the ball in soccer goalkeepers (Piras et al., 2021b; Piras et al., 2021a). This investigation differs from the others that have studied the role of microsaccades in a sports context. This experiment followed an ecological approach, with a dynamic sequence, under constraints imposed by the opponent, in a far-aiming task.

Another potential explanation for the absence of microsaccades is that movement intention suppresses their occurrence (Betta and Turatto, 2006), especially in a dynamic, information-rich environment where microsaccades may interfere with critical perception. Maybe we will need more cutting-edge instruments to investigate this tiny eye movement, or maybe they are suppressed when the movements of the entire body in a far-aiming task are rapid, ballistic, and involved in a constrained approach. We need to look deeply inside the role of microsaccades in some contexts, such as dynamic interceptive tasks, where the concept of microsaccades might indicate increased focus, heightened preparatory states, or their capacity to achieve a state of readiness before upcoming tasks. The implication is that eye movement registration techniques are slightly limited to indicating the locus of fixation and not necessarily the locus of attention in dynamic team sports situations (Piras, 2025). The role of sports science research is to clarify the relationship between the location of perceptual sources of information, the specific task constraints, and the type of gaze behaviour engaged by the athletes. More work is needed to investigate the further impact of using microsaccades to develop the ability to locate and identify visual information in the environment for the selection and execution of actions.

In dynamic far-aiming tasks, like shooting a soccer ball or during basketball jump shooting, there is often no time for long fixations and, therefore, no time to process a motor program (de Oliveira et al., 2006). In this dynamic sequence, the timing for catching and detecting visual information is critical and limited by the constraints, so the visual search strategy should be used online. Adopting the high-style shooting, the ball is first positioned overhead, followed by the elbow extension until the ball is released. An advantage of the high style is that the shooter can look at the basket from underneath the ball when it is held overhead (Oudejans et al., 2002), allowing online visual control of the final shooting movements between the aiming and the ball flight phases. As a result, players need to pick up the necessary information at precise time intervals at which the information is visually available and can be used to control the action. In the present study, basketball jump shooters prefer to pick up optical information about the basket, maintaining a stable fixation between the end of the catching phase and during most of the aiming phase until the ball is released. Then, just before the ball leaves the athletes' hands, the saccade rates increase exponentially, reaching the highest values (see Figure 4). This could be related to the next phase present in a real match, when the player, after the shot, is ready for the rebound. This happens when the ball hits the rim or the backboard, and then the players fight for the best position to snatch the rebound. To get the

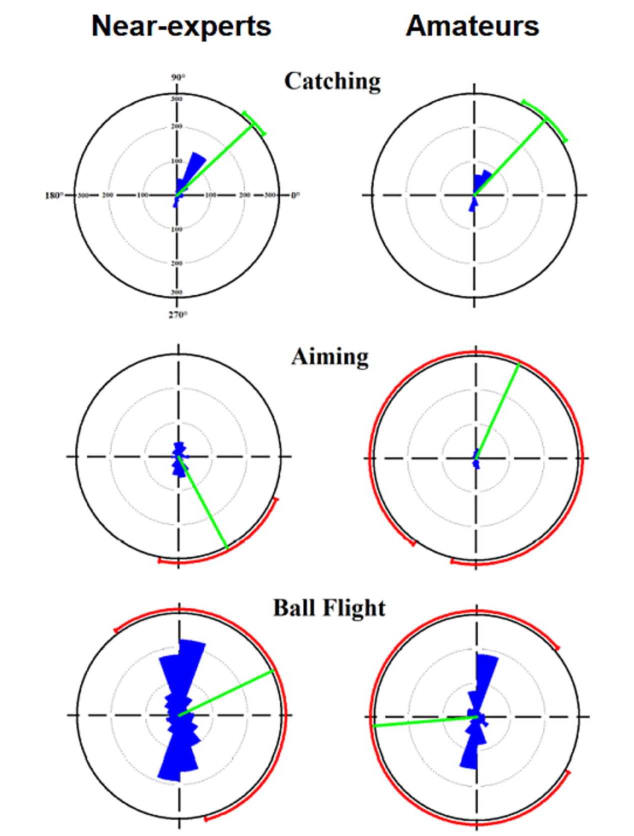

FIGURE 5
Panels represent the mean vector direction of saccades during catching, aiming and ball flight between near-experts (left panels) and amateur (right panels) basketball players. Each angular sector is 20° in width. Green radial thick is the mean vector, and the red ring outside the polar plot is the standard deviation.

rebounding ball, the player is required both to perceive temporal and spatial information through a complex visual field and to react to an opponent player immediately. As illustrated in Figure 5, saccade directions were not informative, except for the catching phase in which players directed their attention toward the player who passed the ball. During aiming and ball flight, the saccade orientations were not uniform, meaning that they did not have a particular direction. Assuming that with the high shooting style, visual information is available until ball release, we expected that gaze fixation could be used for the visual control of the jump shot. The three-point shot is very difficult and fast; from the moment the ball is received until it leaves the hands, elite players release the ball in 600–800 ms, increasing the difficulty for the opponent to intercept it (Vickers et al., 2019). Different studies have investigated the role of vision during jump shots in basketball, and they have ended with different conclusions (Oudejans et al., 2002; de Oliveira et al., 2008; Vickers et al., 2019; Vickers, 1996). One of the first was that of Oudejans et al. (2002), who compared early vs. late vision information when athletes adopted the high shooting style. The authors found that performance with early vision was severely impaired with respect to late visual information. They concluded that when players used a high-style, they raised the ball above their heads and acquired late visual information from the target prior to and during ball release. The final shooting movement is controlled by continuous detection and the use of visual information until the ball is released. A few years later, other authors (de Oliveira et al., 2008), comparing high vs. low shooting style, supported the view that basketball shooting is mainly controlled online by vision, meaning that visual information is picked up and used during movement, rejecting the suppression of the vision during the final shooting phase (Vickers, 1996). More recently, Vickers et al. (2019) have investigated the timing of fixations (early, late), the location of fixations (hoop centre, non-centre) and the effect of the defender during three-point basketball shooting. They found that during the defended condition, the trial duration and the response accuracy were lower than during the undefended condition. Moreover, Vickers et al. (2019) found a low number of fixations during ball release, showing that the three-point shot is taken under such extreme time and defensive pressure that sustaining a fixation until the ball is released is very difficult.

The results of the present study are in accordance with that of Vickers et al. (2019), with a trial duration of about 1,200 ms (without considering the ball flight) and a response accuracy of about 41%. Furthermore, as Figure 4 suggested, the saccade rate showed the highest value during ball release. The three-point shot in basketball is an open skill performed in a movement patterns that is variable and unpredictable and requires athletes to adapt their body movements in response to the dynamic characteristics of the environment. Being a dynamic and constrained task, athletes are subjected to pressure, which can negatively compromise their expectations. More specifically, pressure changes the athletes' attentional mechanisms and memory processes that support performance (Lidor et al., 2022). This phenomenon alters the visual search strategy, observed moving from the first phase in which performers receive the ball without pressure, with a stable fixation and gaze behaviour focused in a particular location, to ball release, in which the opponent pressure increases the instability of the athletes' eyes, with higher saccade rates, amplitudes and peak velocities.

Within the design of the current study, we acknowledge the lack of significant differences in accuracy. This is the main limitation of the current study, related to one of the common problems presented in sports performance: the difficulty of finding players at a very high level (Vickers et al., 2019; Piras et al., 2024). For example, in the National Basketball Association, the number of players that have exhibited a score > 40% in the previous season (2023–24) is only 36 in front of about 560 athletes. The 3-point-field percentage of Stephan Curry was 48.1%.[1]

In conclusion, the results of the present study showed that near-experts exhibited longer fixation durations in both aiming and ball flight phases, with saccades of lower amplitude and peak velocities than amateurs. This result may suggest that these experts have developed an ability to control their eye movements, likely unconsciously, to optimize the visual selection process. Additionally, they seem able to tolerate any potential distractions caused by movement, minimizing its impact on their performance. The time course of saccade rates showed that athletes utilize fixations during the last part of the catching phase and during most of the aiming phase, making the greatest number of saccades when the ball release started.

1 https://www.nba.com/stats/player/201939

Saccade orientations were not informative, maybe because the change of the fixation areas through phases, forced athletes to move their eyes at great retinal eccentricities. This study can be considered a completion of previous studies regarding the timing of vision during a basketball shooting. In the present results, fixations occur early in the shooting action (Vickers et al., 2019; Klostermann et al., 2018), and following an ecological setting, it supported the importance of acquiring late visual information from the target prior and during ball release (de Oliveira et al., 2006; de Oliveira et al., 2008; de Oliveira et al., 2007).

Data availability statement

The datasets presented in this article are not readily available because as the nature of this research is within a high-performance environment, athletes of this study did not agree for their data to be shared publicly, so supporting data are not available. Requests to access the datasets should be directed to AP, alessandro.piras3@unibo.it.

Ethics statement

The studies involving humans were approved by the Bioethics Committee of University of Bologna. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

AP: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

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Conflict of interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Effect of match location on the playing style of teams coached by 'Pep' Guardiola

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Introduction: Analysis in football seeks to find the performance factors that bring teams closer to success.

Methods: This study aims to analyze the playing styles of two teams managed by Pep Guardiola (F.C. Barcelona and Manchester City) based on match location (home or away). Two methods of analysis were used: descriptive statistics through chi-square tests to evaluate game characteristics and the polar coordinates technique to analyze the relationships between the different lines of each team (goalkeeper, defenders, midfielders, and forwards).

Results: The results showed that F.C. Barcelona maintained a consistent playing style regardless of location, exhibiting significant differences only in actions that involved shots or header ($p = 0.035$), with better performance at home. In contrast, Manchester City displayed significantly different performance in action success ($p < 0.001$), level of play elaboration ($p = 0.004$), density ($p = 0.033$), duration ($p = 0.036$), and actions that included a shot ($p = 0.001$) depending on the location. Additionally, qualitative analyses revealed differences in the relationships among the team lines according to match location, with Manchester City displaying more variability in these interactions than F.C. Barcelona.

Discussion: The study concludes that although Guardiola applies a consistent set of strategies, match location has a greater influence on Manchester City's performance, suggesting that this team adjusts its playing style on the basis of contextual conditions. These findings highlight the importance of considering factors such as location when preparing tactics to increase the probability of success in elite football.

KEYWORDS

football, performance analysis, observational methodology, polar coordinates, team sport, playing style

1 Introduction

Football, in its evolution as a sport and cultural phenomenon, underwent significant changes in playing style throughout the 20th and early 21st centuries. Initially, focused on defensive tactics and counterattacks, modern strategies have evolved toward a more balanced approach that values ball possession, progressive buildup from the defense, and complex offensive plays (Barreira et al., 2015). The transformation of football dynamics is due not only to advancements in player technique and performance but also to adaptations to contextual variables such as match location, tournament category, match timing, and the level of the opposing team (Diana et al., 2017; Fernández-Navarro et al., 2018; González-Rodenas et al., 2020). Consequently, today's elite football players must develop high versatility and motor competence, as well as the ability to process information and make decisions quickly and effectively to successfully overcome these challenges (Wallace and Norton, 2014).

Observational methodology (Anguera, 1979) has proven effective for conducting studies of sports behaviors that occur in their natural contexts (Anguera et al., 2017). Thanks to its non-intrusive nature and respect for behavioral spontaneity, it allows for the evaluation and analysis of interaction relationships among different players, as well as the behaviors that emerge from them at both individual and collective levels. Through this methodology, it is possible to identify various analytical techniques applicable in the sports world (Anguera and Hernández-Mendo, 2015), which have led to significant findings. These techniques have already been applied in previous football studies (Castañer et al., 2013; Pic, 2018) with meaningful applied results, enabling important contributions regarding team performance indicators (Mićović et al., 2023) and the playing styles developed according to different contexts (Castellano and Pic, 2019), thus aiding in the search for strategies that lead to success in elite football.

One of the most studied variables in this regard has been match location (Brito de Souza et al., 2019; Kong et al., 2022) and how it affects team performance. Playing a home match impacts various factors that involve different ways of playing. For example, Almeida et al. (2014) reported that home teams, compared with away teams, tend to defend in more advanced areas of the field, and this approach is more effective when analyzing higher-ranked teams versus those whose standing is lower. Similarly, Diana et al. (2017) identified more complex and elaborate attacking patterns in home matches than in away games. Lago-Peñas and Lago-Ballesteros (2011) even showed that home teams exhibit superior performance in terms of technical and tactical execution. In general, playing at home provides an advantage, and teams may severely alter their playing style on the basis of location (Sarmento et al., 2014).

La Liga and the Premier League offer paradigmatic examples of contexts that, despite sharing certain similarities, present distinctive characteristics and playing styles (Cooper and Pulling, 2020; Nagy et al., 2023). While La Liga has traditionally been known for its technical, possession-based football, the Premier League is noted for its fast pace and emphasis on physicality. Comparisons between these two competitions have been conducted on numerous occasions (Fernández-Navarro et al., 2016; González-Rodenas et al., 2021; Gouveia et al., 2023).

Within this framework, the figure of Pep Guardiola stands out as a unique case study. Having coached teams in both leagues and achieved success in each provides an ideal context to explore how a consistent set of strategies and tactical philosophies can manifest and adapt in leagues with such different characteristics. Previous studies (Immler et al., 2021) have compared playing styles among elite coaches, but few works have examined the evolution or transformation of a coach's team playing characteristics over time across different competitions, with match location as the object of study.

The purpose of the present research was to evaluate the playing styles of two teams coached by Pep Guardiola (F.C. Barcelona and Manchester City) based on match location (home or away). Descriptive statistics, through chi-square tests, were used to understand their playing characteristics, and qualitative analysis, using the technique of polar coordinates, was applied to discover the interline relationships they produced (goalkeeper -GK-, defenders -DEF-, midfielders -MID-, and forwards -FW-) within each team's formations. Thus, the aim was to determine whether these teams maintained a stable playing style regardless of where they played their matches or if they were compelled to adapt their match tactics.

2 Materials and methods

The present study corresponded to an observational design of the nomothetic, punctual, and multidimensional type (N/P/M): nomothetic because the two teams were observed as different observational units; punctual because a count of the players' actions with the ball was made without aiming to conduct a global follow-up of the teams; and multidimensional due to the sequential heterogeneity of possibilities in the different game situations (Anguera et al., 2011).

2.1 Participants

An observational sampling with an intentional or convenience character was carried out (Otzen and Manterola, 2017) involving the two teams under study: F.C. Barcelona and Manchester City. The seasons in which both teams scored the highest number of league goals under Pep Guardiola's management. At the start of the study these were the 2011/2012 season for F.C. Barcelona (114 goals) and the 2018/2019 season for Manchester City (95 goals). To enhance the validity of the sample, matches played against the top six teams at the end of the season in their national regular competitions were selected (Castellano et al., 2013), including both home and away games (Table 1).

The preparation of this manuscript did not require informed consent or the approval of any ethics committee, complying with the requirements of the National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research (1979), as it involves observation of public footage where the subjects have no reasonable expectation of privacy and do not involve any staged intervention by the researcher or direct interaction with individuals. Similarly, notably, the fundamental ethical principles for research with human beings have been followed in accordance with the Declaration of Helsinki (World Medical Association, 2021; Bošnjak, 2001; Tyebkhan, 2003).

2.2 Observational instrument

The observation instrument used in this study is the one designed by Maneiro and Amatria (2018), developed as an '*ad hoc*' instrument at its

TABLE 1 Observed matches of each team.

Matches of F.C. Barcelona 2011/2012	Matches of Manchester City 2018/2019
Valencia – Barcelona (A)	Arsenal – Manchester City (A)
Barcelona – Atlético de Madrid (H)	Liverpool – Manchester City (A)
Barcelona – Levante (H)	Tottenham – Manchester City (A)
Real Madrid – Barcelona (A)	Manchester City – Manchester United (H)
Málaga – Barcelona (A)	Chelsea – Manchester City (A)
Barcelona – Valencia (H)	Manchester City – Liverpool (H)
Atlético de Madrid – Barcelona (A)	Manchester City – Arsenal (H)
Levante – Barcelona (A)	Manchester City – Chelsea (H)
Barcelona – Real Madrid (H)	Manchester City – Tottenham (H)
Barcelona – Málaga (H)	Manchester United – Manchester City (A)

(H) = Home; (H) = Away (A).

TABLE 2 Variables evaluated.

Variable	Definition	Measurement
Success of actions (González-Rodenas et al., 2023)	Qualitative evaluation of the result of each player's technical interaction with the ball during game actions, considering an action successful if it subsequently reaches a teammate or ends in a goal. Actions that end in loss, game stoppage, or occasional interception are considered unsuccessful, in accordance with the criteria of the observational instrument.	Yes/No
Elaboration of offensive sequences (Amatria et al., 2019; Tenga et al., 2009)	Quantification of the total number of passes made in each offensive sequence, as an indicator of the level of construction and coordination of play.	0–1 (nonexistent); 2–3 (very low); 4–5 (low); 6–10 (medium); 11–15 (high); 16–20 (very high); 21 or more (maximum)
Density of offensive sequences (Amatria et al., 2019)	Measurement of the number of participants involved in each offensive sequence, providing a metric for the density of on-field collaboration.	0–1 (nonexistent); 2–3 (very low); 4–5 (low); 6–10 (medium); 11–15 (high); 16 or more (very high)
Duration of offensive sequences (Tenga and Sigmundstad, 2011)	Recording of the temporal duration, in seconds, of the offensive sequences to analyze their sustaining period.	0–5 s (low); 6–11 s (medium); 12 s or more (high)
Shot or header (Hewitt et al., 2016)	Recording and quantification of the occurrence of shots or attempts during offensive sequences, as an indicator of offensive completion.	Yes/No

creation. It was based on a field format combined with category systems (Anguera et al., 2020) because the design is multidimensional and each of the criteria unfolds a list of categories, fulfilling the requirements of exhaustiveness and mutual exclusivity (Anguera and Hernández-Mendo, 2013).

Subsequently, once all ball-in-play actions were recorded, variables related to the developed playing style were examined, focusing on the success of the technical actions performed, the level of elaboration and density of the plays, duration, and the volume of shots or attempts (Table 2; Pueyo et al., 2024).

2.3 Recording and coding

Data recording (Hernández-Mendo et al., 2014) was performed via the software Lince version 1.4 (Gabin et al., 2012). This software was used for recording and collecting all data, and multievents occurred, understanding the latter as each unit of record within the program. The data obtained are time-based and concurrent, that is, type IV (Bakeman, 1978). Subsequently, the GSEQ software version 5.1 (Bakeman and Quera, 2011) was used to perform sequential lag analysis. The data were introduced into a second program called Hoisan version 1.2 (Hernández-Mendo et al., 2012), with which the corresponding results of the polar coordinate analysis were obtained.

2.4 Data quality control

The researchers who participated in the observations of this study were both graduates in physical activity and sports sciences, with extensive experience as coaches in the context of football and in the development and application of observational methodology in this sport. Evidence of this is the previously published works by the manuscript's authors (Álvarez Medina et al., 2020; Amatria et al., 2021; Pueyo et al., 2024).

To increase the quality of the data for this work, the principal investigator received specific training in the methodology and handling of the recording instrument, aligning with the guidelines proposed by Losada and Manolov (2015) as well as Anguera (2003). This emphasizes the importance of adequate training for the observer in studies of this nature, ensuring an appropriate level of competence and understanding in the research context.

To guarantee the validity of the data obtained through the observational instrument, the GSEQ software version 5.1 (Bakeman and Quera, 2011) was used. Through this software, Cohen's Kappa coefficient (Cohen, 1960) was calculated a statistical measure that allowed for an intra-observer analysis in which the data records made at two distant time periods (1 week apart) were compared. Block 1 of the data evaluated corresponds to all the actions that make up the sample, whereas Block 2 comprises 15% of the recorded sequences (Arroyo et al., 2023). The concordance between these two blocks yielded a coefficient of 0.95 in the overall computation of the evaluated dimensions. Likewise, to provide greater robustness and achieve a higher degree of reliability, consultative concordance was carried out (Arana et al., 2016). This qualitative method eliminates the confusion generated by two different interpretations and consists of presenting to a second observer only the discrepant observations between both blocks of records without knowing to which one the recording error corresponds, generating a new data block (Block 3). The observer decides on the basis of their judgment, which of the records constitutes the definitive observation, thus overcoming any limitations inherent to intra-observer concordance. The levels of reliability obtained are within the range classified as "almost perfect" according to the criteria established by Landis and Koch (1977), thereby reinforcing the solidity of the results obtained in the research.

2.5 Data analysis

Two types of analyses were carried out in this study. On the one hand, a quantitative analysis was performed via Pearson's chi-square statistic (χ^2), following the formula: $\chi^2 = \Sigma_{i=1\kappa} \Sigma_{j=1\kappa} \left[\left(F_{ij} - F_{ij} \right)^2 / F_{ij} \right]$. The level of significance in the data treatment was set at ($\rho < 0.05$). For this purpose, SPSS v.27 software was used.

On the other hand, to perform the qualitative analysis, the technique of polar coordinates was used. This analytical methodology is grounded in the Zsum proposed by Cochran (1954). This principle is based on the notion that the sum of a series of N independent z scores follows a normal distribution characterized by a mean $Z = 0$ and a standard deviation $s = \sqrt{N}$. Thus, the Zsum statistic is defined as $Zsum = \Sigma_{i=/}^{m} z / \sqrt{n}$ (where n is the number of lags involved). This statistic is crucial, as it facilitates the quantification of the associative strength between different behaviors, as noted by Sackett (1980).

Anguera (1997) subsequently proposed an evolution of this technique by introducing the retrospective perspective into the analysis. Polar coordinate analysis allows the elucidation of the relationships of excitation or inhibition between the focal behavior -that is, the behavior under analysis- and the other behaviors that make up the taxonomic system, referred to as conditioned behaviors. This analysis is carried out both from a prospective approach (from +1 to +5) and from a retrospective perspective (from −1 to −5), resulting in a specific vector for each behavior associated with the focal behavior, each characterized by a particular angle and radius. According to these angular premises, the vector can be located in four sectors or quadrants (Figure 1). If it is in quadrant I, there is mutual excitation between the focal behavior and the conditioned behavior. In quadrant II, the focal behavior inhibits the conditioned behavior, and the conditioned behavior excites the focal behavior. If it is located in quadrant III, there is mutual inhibition of the behaviors. Moreover, if the vector falls into quadrant IV, the focal behavior excites the conditioned behavior, and the conditioned behavior inhibits the focal behavior.

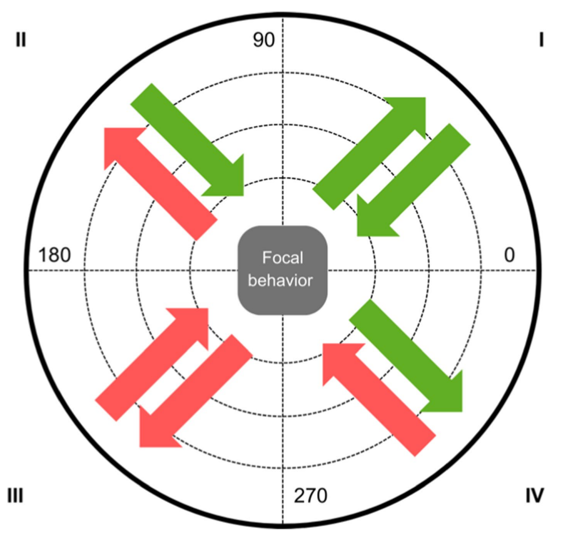

FIGURE 1
Graphical representation of the excitation or inhibition relationships between the focal behavior and the conditioned behaviors according to the quadrant in which they are located. In green, when it is an excitatory behavior. In red, when it is an inhibitory behavior.

3 Results

A total of 21,377 multievents were recorded, understood as each unit of recording performed. This resulted in 2,356 offensive sequences: 630 and 623 from F.C. Barcelona as home and away teams and 526 and 577 from Manchester City, respectively.

Table 3 shows the results of the variables evaluated for each team based on location. The success of actions indicates that there are no significant differences in the Spanish team, with even a slight increase in success when playing away. In contrast, the English team shows a significant decrease in success when playing away matches ($\rho < 0.001$).

With respect to the level of elaboration, density, and duration, F.C. Barcelona shows similar results regardless of location, with a tendency toward slightly higher values when playing at home. On the other hand, Manchester City presents significant differences in elaboration ($\rho = 0.004$), density ($\rho = 0.033$), and duration of their play ($\rho = 0.036$), with much higher values in home matches than in away matches, where their offensive actions are less elaborate, dense, and enduring.

Finally, concerning the volume of plays with shots or headers on goal, significant differences are observed in both teams. Both F.C. Barcelona ($\rho = 0.035$) and Manchester City ($\rho = 0.001$) have higher levels of action completion when matches are played at home compared to when they play as visitors.

The results obtained through the polar coordinates analysis of the relationships established between the different lines that compose each team's structure are shown in Table 4 (F.C. Barcelona) and Table 5 (Manchester City). Each line acting as a focal behavior concerning the rest of the team is presented.

First, the 'GK' (Goalkeeper) category as the focal behavior in both teams, in contrast to the 'DEF' (Defenders), 'MID' (Midfielders), and 'FW' (Forwards) categories identified as conditioned behaviors. This approach was designed to examine the goalkeeper's predisposition to play in relation to the other lines that compose the game structure during matches.

With respect to the results (Table 4 and Figure 2), in the case of F.C. Barcelona, the conditioned category 'DEF' is located in quadrant I, with a radius length of 5.95 and angle of 34° when playing at home and a radius of 6.4 and angle of 43.81° when playing away. This finding indicates that focal behavior activates the presence of conditioned behavior in both the prospective and retrospective planes. The 'MID' and 'FW' categories are located in quadrant III in both locations, indicating that the focal behavior inhibits the presence of the conditioned behavior in both planes. The values associated with these categories are radii of 1.97 and 4.66 and angles of 235.08° and 209.29°, respectively, when playing at home and radii of 4.91 and 3.45, with angles of 236.25° and 211.26°, respectively, when playing away.

In the case of Manchester City (Table 5 and Figure 2), when the match is at home, the 'DEF' category is located in quadrant I, with a radius of 6.69 and an angle of 45.22°, and the 'MID' and 'FW' categories are positioned in quadrant III, with radii of 3.62 and 5.18 and angles of 219.39° and 232.47°, respectively. Conversely, when playing away, the 'DEF' and 'FW' categories remain in the same quadrants (radii of 4.54 and 6.48 and angles of 55.48° and 214.14°), but the 'MID' category is in quadrant IV with a radius of 3.14 and an

TABLE 3 Summary of results based on home and away matches.

Variable		F.C. Barcelona			Manchester City		
		Home	Away	*p*-value	Home	Away	*p*-value
Success of actions	Success	81.6%	81.8%	0.786	82.5%	78.9%	<0.001
	No success	18.4%	18.2%		17.5%	21.1%	
Level of elaboration	Nonexistent	8.9%	9.0%	0.729	7.8%	12.5%	0.004
	Very low	22.5%	26.0%		31.2%	31.0%	
	Low	20.0%	17.3%		14.8%	19.4%	
	Medium	27.6%	26.8%		21.9%	16.6%	
	High	12.7%	11.7%		12.9%	13.3%	
	Very high	4.6%	4.7%		5.9%	3.3%	
	Maximum	3.7%	4.5%		5.5%	3.8%	
Play density	Nonexistent	10.5%	11.2%	0.634	9.7%	14.9%	0.033
	Very low	24.6%	26.0%		33.5%	32.4%	
	Low	20.3%	16.5%		13.9%	16.8%	
	Medium	26.0%	27.0%		20.5%	18.2%	
	High	11.6%	11.3%		12.9%	11.1%	
	Very high	7.0%	8.0%		9.5%	6.6%	
Play duration	Low	21.1%	23.0%	0.665	24.3%	27.2%	0.036
	Medium	22.7%	21.1%		22.6%	27.4%	
	High	56.2%	55.9%		53.0%	45.4%	
Plays with shot/header	Yes	12.7%	9.0%	0.035	13.5%	7.5%	0.001
	No	87.3%	91.0%		86.5%	92.5%	

*$p < 0.05$.

TABLE 4 Results of the polar coordinates analysis for different focal categories in relation to the rest of the lines forming FC Barcelona's structure both home and away.

F.C. Barcelona – Home					F.C. Barcelona – Away				
Focal cat.	Cat.	Quadrant	Radius	Angle	Focal cat.	Cat.	Quadrant	Radius	Angle
GK	DEF	I	5.95**	34	GK	DEF	I	6.4**	43.81
	MID	III	1.97*	235.08		MID	III	4.91**	236.25
	FW	III	4.66**	209.29		FW	III	3.45**	211.26
DEF	GK	I	5.95**	56	DEF	GK	I	6.4**	46.19
	DEF	I	8.71**	45		DEF	I	6.2**	45
	MID	III	3.23**	247.52		MID	III	3.31**	260.51
	FW	III	8.51**	222.78		FW	III	7.22**	211.96
MID	GK	III	1.97*	214.92	MID	GK	III	4.91**	213.75
	DEF	III	3.23**	202.48		DEF	III	3.31**	189.49
	MID	I	2.05*	45		MID	I	1.71**	45
	FW	I	2*	5.12		FW	I	3.92**	8.01
FW	GK	III	4.66**	240.71	FW	GK	III	3.45**	238.74
	DEF	III	8.51**	227.22		DEF	III	7.22**	238.04
	MID	I	2*	84.88		MID	I	3.92**	81.99
	FW	I	9.51**	45		FW	I	6.2**	45

TABLE 5 Results of the polar coordinates analysis for different focal categories in relation to the rest of the lines forming Manchester City's structure both home and away.

Manchester City – Home					Manchester City – Away				
Focal cat.	Cat.	Quadrant	Radius	Angle	Focal cat.	Cat.	Quadrant	Radius	Angle
GK	DEF	I	6.69**	45.22	GK	DEF	I	4.54**	55.48
	MID	III	3.62**	219.39		MID	IV	3.14**	290.42
	FW	III	5.18**	232.47		FW	III	6.48**	214.14
DEF	GK	I	6.69**	44.78	DEF	GK	I	4.54**	34.52
	DEF	I	10.18**	45		DEF	I	10.09**	45
	MID	III	4.84**	208.25		MID	III	4.27**	215.19
	FW	III	10.4**	235.73		FW	III	9.55**	229.16
MID	GK	III	3.62**	230.61	MID	GK	II	3.14**	159.58
	DEF	III	4.84**	241.75		DEF	III	4.27**	234.81
	MID	I	3.64**	45		MID	I	3.93**	45
	FW	I	3.89**	75.69		FW	I	1.66	28.15
FW	GK	III	5.18**	217.53	FW	GK	III	6.48**	235.86
	DEF	III	10.4**	214.27		DEF	III	9.55**	220.84
	MID	I	3.89**	14.31		MID	I	1.66	61.85
	FW	I	10.81**	45		FW	I	12.33**	45

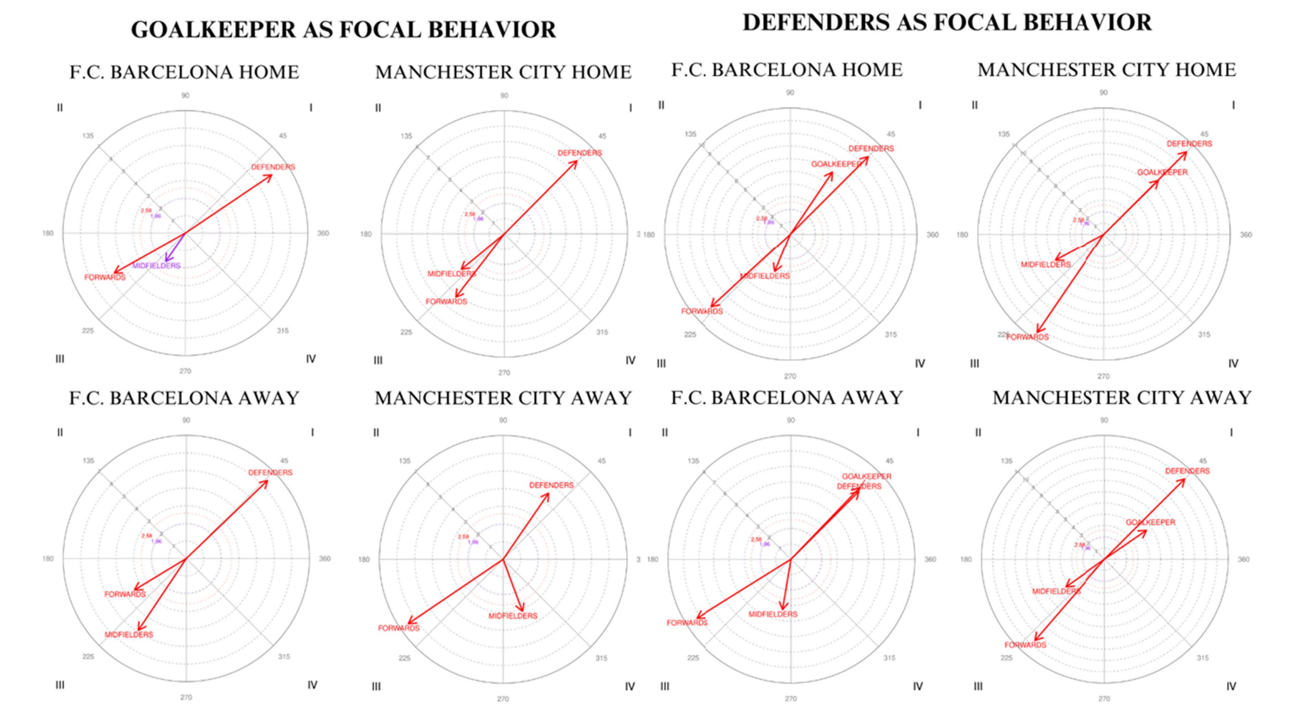

FIGURE 2
Behavioral map representation establishing the goalkeeper and defense categories as focal behaviors in relation to the lines structuring the team.

angle of 290.42°. This implies that focal behavior activates the presence of conditioned behavior in the prospective plane but not in the retrospective plane.

Second, the focal behavior was set as 'DEF' (Defenders) and related to the remaining categories that configure the team's structure, including the defensive line itself: 'GK', 'DEF', 'MID', and 'FW'. The objective of this approach is to investigate the playing predisposition exhibited by the defensive line in relation to the other lines that make up the team's tactical structure during matches.

The results obtained (Table 4 and Figure 2) for F.C. Barcelona show that the categories 'GK' and 'DEF' are located in quadrant I for both home and away matches, indicating that focal behavior activates the presence of conditioned behavior in both the prospective and retrospective planes. The corresponding values are radii of 5.95 and 8.71 with angles of 56° and 45°, respectively, for home matches and radii of 6.4 and 6.2 with angles of 46.10° and 45° when playing away. In contrast, the categories 'MID' and 'FW' are situated in both cases in quadrant III, where the focal behavior inhibits the presence of the conditioned behavior in both planes. The values associated with these categories are radii of 3.23 for midfielders and 8.51 for forwards, with angles of 247.52° and 222.78° at home, and radii of 3.31 and 7.22, with angles of 260.51° and 211.96° away, respectively.

In the case of Manchester City (Table 5 and Figure 2), the categories 'GK' and 'DEF' are located in quadrant I, with radii of 6.69 and 10.18 and angles of 44.78° and 45° at home and radii of 4.54 and 10.09 with angles of 34.52° and 45° when playing away. The categories 'MID' and 'FW', on the other hand, are found in quadrant III, with radii of 4.84 and 10.4 and angles of 208.25° and 235.73° at home and radii of 4.27 and 9.55 with angles of 215.19° and 229.16° when playing away.

In the third segment of the analysis, the midfielders (MID) were established as the focal behavior, both in relation to themselves and to the other lines on the field: 'GK', 'DEF', 'MID', and 'FW'. This approach aims to evaluate how the midfield line interacts with the other positions that compose the tactical structure throughout the match.

The results obtained (Table 4 and Figure 3) for F.C. Barcelona indicate that the categories 'GK' and 'DEF' are located in quadrant III, both at home and away, with radii of 1.97 and 4.91 and angles of 214.92° and 213.75°, respectively, for the 'GK' category, and radii of 3.23 and 3.31, with angles of 202.48° and 189.49°, respectively, for the 'DEF' category. In this context, focal behavior inhibits the presence of conditioned behavior in both the prospective and retrospective planes. On the other hand, the categories 'MID' and 'FW' are in quadrant I, activating the conditioned behavior in both planes. The corresponding values are a radius of 2.05 and an angle of 45° for the midfielders, a radius of 2 and an angle of 5.12° for the forwards in home matches, and radii of 1.71 and 3.92 with angles of 45° and 8.01° for the 'MID' and 'FW' when playing away.

With respect to Manchester City (Table 5 and Figure 3), the categories 'GK' and 'DEF' are situated in quadrant III, with radii of 3.62 and 4.84 and angles of 230.61° and 241.75°, respectively, when playing at home and radii of 3.14 and 4.27, with angles of 159.58° and 234.81°, respectively, when playing away. The categories 'MID' and 'FW', in contrast, appear in quadrant I in both locations, with a radius of 3.64 and an angle of 45° for the former, a radius of 3.89 and an angle of 75.69° for the latter at home, and radii of 3.93 and 1.66 with angles of 45° and 28.15°, respectively, when playing away.

In the fourth and final segment of the study, the forwards (FW) category was adopted as the focal behavior to analyze its interaction with the other team lines along with itself: 'GK', 'DEF', 'MID', and 'FW'. This approach aims to explore the tactical predisposition of the forward line in relation to the other positions that compose the team's structure throughout the match.

In the case of F.C. Barcelona, as represented in Table 4 and Figure 3, the categories 'GK' and 'DEF' are located in quadrant III both at home and away. This finding indicates that focal behavior, represented by the forwards, inhibits the presence of conditioned behavior in both the prospective and retrospective planes. The specific values reflect radius lengths of 4.66 and 8.51 and angles of 240.71° and 227.22°, respectively, when playing at home and 3.45 and 7.22 with angles of 238.74° and 238.04°, respectively, when playing

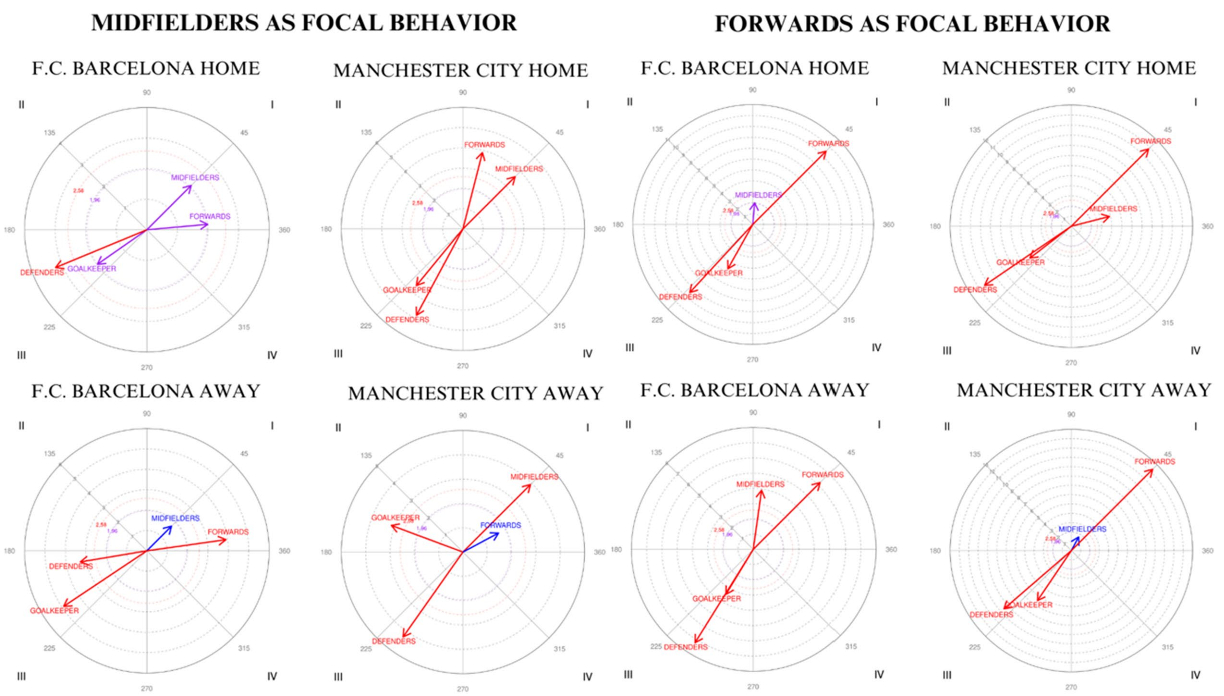

FIGURE 3
Behavioral map representation establishing the midfielder and forward categories as focal behaviors in relation to the lines structuring the team.

away. On the other hand, the categories 'MID' and 'FW' are found in quadrant I, which means that the focal behavior activates the presence of the conditioned behavior in both planes. With respect to the midfield line, values of 2 in length and an angle of 84.88° are observed, whereas for the forwards, the values are 9.51 in length and 45° in angle at home. Conversely, when playing as visitors, the radii are 3.92 and 6.2, with angles of 81.99° and 45°, respectively, for these two conditioned categories.

Regarding Manchester City, the categories 'GK' and 'DEF' are also positioned in quadrant III, with radius lengths of 5.18 and 10.4 and angles of 217.53° and 214.27° when playing at home and radii of 6.48 and 9.55 with angles of 235.86° and 220.84°, respectively, when playing away. Moreover, the categories 'MID' and 'FW' are located in quadrant I, with radius lengths of 3.89 and 10.81, angles of 14.31° and 45° at home, and lengths of 1.66 and 12.33 along with angles of 61.85° and 45° when playing away from their own stadium.

4 Discussion

The objective of the present research is to determine whether the playing style developed by teams coached by Pep Guardiola remains stable regardless of the match location or if it is influenced by contextual variables that alter its game dynamics. The study reveals notable differences in the playing methodology of F.C. Barcelona and Manchester City under Guardiola's leadership: the Spanish team's playing style appears to be stable despite changes in setting, whereas the English team's tactics show significant adaptability depending on whether they play at home or away.

With respect to the descriptive results, Manchester City's evaluated parameters exhibit significant variations on the basis of match location, in stark contrast to F.C. Barcelona, whose comparative analysis shows remarkable consistency, except in the aspect of shots on goal, where a significant difference is identified. The variability in the playing styles between both teams can be attributed to multiple factors.

Initially, it was worth highlighting the divergence in the rosters of both clubs. F.C. Barcelona, during a period when its playing style and dominance were the subject of extensive academic analysis (Buldú et al., 2019; Chassy, 2013), had players ranked among the best in European football, whose skills have been the subject of various investigations (Castañer et al., 2016; Lapresa et al., 2020; Maneiro et al., 2019). These teams have already been studied in previous research (Pueyo et al., 2024), confirming the difference in playing style between the two teams. On the other hand, considering the competitive context of each team is essential. Spain's Primera División is distinguished by more combinative play and prolonged ball possession (González-Rodenas et al., 2023), while the English Premier League leans toward a more direct and vertical style, influenced by the intense pressing that characterizes teams in this league (Mitrotasios et al., 2019). The differences between these competitions have been extensively examined in the literature (Cooper and Pulling, 2020; Nagy et al., 2023), providing a basis for understanding the discrepancies in the methods used by teams participating in both competitions.

Moreover, the idea that playing at home confers an advantage in football is well accepted in the literature, with evident differences in the number of goals scored, the effectiveness of technical actions, and the probability of victory at the end of the match (Almeida et al., 2014; Diana et al., 2017; Sarmento et al., 2014). In the case of F.C. Barcelona, indicators of success in actions performed, the elaboration of plays, as well as their density and duration, maintain notable consistency both in matches at their stadium and those played away. In contrast, Manchester City's analysis reveals a significant increase in the effectiveness, elaboration, density, and durability of plays when they compete on their own ground. This pattern suggests that playing at home enhances the team's ability to generate more complex and sustained sequences of play that culminate more successfully. Additionally, the last parameter examined, referring to the percentage of offensive flow generated, corroborates that both teams, when playing at home, increase their ability to finish play, which is essential for achieving the ultimate goal in football: scoring.

The exploration of interline relationships through polar coordinate analysis -a technique previously applied in this context (Maneiro et al., 2018) corroborates the observed trends. A notable consistency is highlighted in the defensive line of both teams, which, despite experiencing variations in intensity, maintains a uniform vectorial distribution, suggesting that the function of these players with the ball remains unaltered, regardless of match location. However, a more detailed examination of the other lines constituting the teams reveals significant contrasts, especially in Manchester City. This analysis reveals that, in away game situations, the team's goalkeeper establishes connections with midfielders predominantly in quadrant IV, unlike quadrant III, which is observed when playing at home, where their relationships are mutually inhibited. This condition may indicate that, under high-pressure situations, the goalkeeper plays with the midfield line that drops back to receive the ball or opts to bypass the defensive line, facilitating forward ball movement through direct links with midfielders as a strategy to overcome opposing pressure lines.

Focusing on the midfield line, similar vectorial trends are observed in F.C. Barcelona, whereas notable differences are detected in Manchester City. The midfielders of the Catalan team maintain interactions mainly with their own midfield line and with the forwards, showing a greater preference for the latter in away matches, suggesting a tendency toward greater verticality in play. In contrast, the English team, although exhibiting behavior similar to that of F.C. Barcelona in home matches, shows a different relationship when playing away, with the goalkeeper positioning in quadrant II, reflecting the reception of the ball directly from the goalkeeper as a tactical resource. Although there is a tendency toward interaction with the forward line in quadrant I, it does not reach statistical significance, indicating that, while present, the relationship between these two lines is not predominantly strong.

Regarding the forward line as the focal behavior, the vectors consistently occupy the same quadrants under all circumstances, differing only in the intensity of their interactions. The relationship between forwards and midfielders, situated in quadrant I, reflects mutual excitation with the focal behavior. However, the intensity of this interaction with F.C. Barcelona's midfielders in home matches, although significant, is less pronounced than that in away matches. In contrast, Manchester City demonstrates significant connections both with forwards and midfielders in quadrant I and with defenders and the goalkeeper in quadrant III in home matches. However, in away game contexts, the significant relationship with the midfielders diminishes, with the interaction among forwards predominating when they are in possession of the ball.

The study is not without limitations in adequately contextualizing the findings. One relates to the sample size employed. The analysis focused on ten matches of each team, played against the top teams in their respective competitions, suggesting that the results obtained should be interpreted with caution and considered preliminary until they can be complemented and validated by future studies with larger samples against rivals of various standings and in different competitions, thereby expanding the scope of analysis and corroborating the observed findings. Additionally, this study did not explicitly examine the impact that the opponent team's behavior, particularly their ball pressure at each moment, may have on the playing style. Lastly, this manuscript lacks other analyses that could have been of interest, such as T-Patterns (Pic and Jonsson, 2021), which might have yielded clearer results regarding the objective of the study. Future research may focus on exploring how the location and characteristics of different competitions affect teams' tactical approaches, as well as comparing the strategies adopted by Pep Guardiola with those of other coaches of similar styles to assess adaptability in different contexts.

5 Conclusion

The aim of this research was to analyze the variations in the playing styles of two teams coached by Pep Guardiola to determine differences in their performance on the basis of whether they played their matches at home or away. The results indicate that F.C. Barcelona's playing methodology remains consistent, highlighting greater completion of plays in their own stadium and notable stability in the interrelations among the various positional lines that compose their formation, regardless of match location. In contrast, Manchester City shows significant variability in all evaluated aspects, offering a higher percentage of success in their actions, as well as more elaborate, dense, and prolonged offensive sequences when playing at home. Furthermore, with the exception of the defensive line, the other positional lines of the team show variations in their interrelations depending on the match location. Therefore, the coach under study does not always maintain a singular playing style, and, depending on different competitive variables—such as the type of competition, the squad, or match location—it becomes necessary to adapt the playing style to the demands of the situation.

The practical applications arising from this study involve equipping teams with tactical alternatives on the basis of the match context. Playing at home or away can constitute a contextual factor that affects the development and style of play; therefore, preparing players to confront these performance constraints will be important for increasing the chances of victory.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent from the patients/participants or patients/participants' legal guardian/next of kin was not required to participate in this study in accordance with the national legislation and the institutional requirements.

Author contributions

LP: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. VM: Conceptualization, Investigation, Visualization, Writing – review & editing. JÁ: Conceptualization, Project administration, Supervision, Validation, Writing – review & editing. AS: Supervision, Writing – review & editing. MA: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declare that Gen AI was used in the creation of this manuscript. To improve the structure and clarity of the text.

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Construction of 2022 Qatar World Cup match result prediction model and analysis of performance indicators

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This research investigates the influence of performance metrics on match outcomes and constructs a predictive model using data from the Qatar World Cup. Employing magnitude-based decision and an array of machine learning algorithms, such as Decision Trees, Logistic Regression, Support Vector Machines, AdaBoost, Random Forests, and Artificial Neural Network, we examined data from 59 matches, excluding extra time. Fourteen performance indicators were integrated into the model, with two types of match outcomes—winning and non-winning—serving as the output variables. The ANN model exhibited the highest predictive performance, achieving an accuracy of 75.42%, an AUC of 76.96%, a precision of 72.73%, a recall of 65.31%, a specificity of 77.03%, and an F1 score of 68.82%. SHAP analysis revealed that "On Target", "Shooting Opportunity", and "Ball Progressions" were the most influential features. These findings underscore the critical role of shooting accuracy and the creation of scoring opportunities in determining match outcomes. Consequently, this study developed an accurate model for predicting match outcomes and meticulously analyzed the match performance. Coaches should prioritize the sensitive indicators identified in this study during training and structure training sessions accordingly.

KEYWORDS

World Cup, football, match performance analysis, machine learning, magnitude-based decision

1 Introduction

Football performance analysis aims to determine the quantitative relationship among various aspects, links, and components of the system as well as their characteristics by using data to reflect the technical, tactical, and other aspects of the game (1). In other words, it is a research method for investigating the game system. With the rapid development of wearable devices and optical tracking technology, performance analysis has transitioned from simple descriptive statistics to in-depth analysis based on electronic information and artificial intelligence. This technological empowerment promotes the application of artificial intelligence in the development of performance analysis. The fusion of multi source heterogeneous data can facilitate the application of performance analysis in quantitatively studying performance dimensions that were previously difficult to quantify (2). In traditional game analysis research, technical and tactical indicators are often separated from factors such as time, location, and opponents, resulting in a lack of validity and reliability in the construction of technical and tactical evaluation systems. To address this deficiency the data collected for technical, tactical, and physical indicators should cover category, effect, time, location, and defensive intensity aspects (3). As a carrier of technical, tactical, and physical performance information, indicators that reflect the intrinsic and extrinsic characteristics and patterns of the game can guide the team's training and competition (4). The correlation between passes, playing formations, and technical-tactical elements is crucial for understanding team performance during competitions. Offensive formations tend to increase possession and passing accuracy, while defensive formations rely on counterattacks and long passes. High-performing teams also demonstrate better balance in player positioning and pressing strategies, contributing to greater control in key areas of the field (5–7).

With the continuous development of computer science and data mining technology, machine learning algorithms based on artificial intelligence have been proven to predict match outcomes and analyze match characteristics. For example, new supervised models, such as artificial neural networks (ANNs), support vector machines (SVMs), and random forests (RFs) have demonstrated excellent predictive performance in different domains. In recent years, machine learning has been utilized to predict the outcome of sports matches, such as K-nearest neighbors (KNN) algorithm, RF, logistic regression (LR), and SVM (8–10). These models incorporated 9 features and 640 data points, with LR achieving the highest prediction accuracy of 63% (11). Another study applied six different machine learning algorithms (naive Bayes, Bayesian networks, logit boost, KNN, RF, and NN) to predict the results of UEFA Champions League matches, with the NN model achieving a prediction accuracy of 68.8% for win, draw, and loss outcomes (12). In recent years, scholars have used the Bayesian model averaging approach to analyze the relative importance of performance-related factors in determining match outcomes in the "Big Five" European football leagues (English Premier League, German Bundesliga, Spanish La Liga, French Ligue 1, and Italian Serie A) from the 2012/2013 to 2014/2015 seasons. The number of saves made by goalkeepers could be an important factor for predicting team performance; however, it had been overlooked in previous research (13). Besides predicting match outcomes, machine learning can analyze the relationship between indicators and prediction outcomes. For instance, Random Forest (RF) or Decision Tree (DT) models calculate indicators importance using Gini index and information gain (14). SHAP (SHapley Additive exPlanations) is also a powerful and unified metric for interpreting machine learning model outputs. It provides a consistent approach to understanding the impact of indicators on model predictions. This method allows for the fair allocation of each indicator's influence on the prediction, taking into account the potential interactions and dependencies between indicators. Additionally, LIME (Local Interpretable Model-agnostic Explanations) achieves indicators importance analysis by fitting a locally interpretable model around a specific data point (15, 16). These methods offer different perspectives and techniques for interpreting indicators importance, widely used in the explainability research of various machine learning models. Currently, machine learning algorithms commonly used in performance analysis in competitions include ANN, LR, decision trees (DT), RF, SVM, and AdaBoost (17–19). Therefore, selecting more scientific statistical models and inference methods to predict the development trends of tactics and physical demands can improve the decision-making abilities of athletes and coaches, the direction and targeting of training, and the application value of match performance analysis.

Considering the aforementioned points, this study focuses on the 64 matches of the 22nd World Cup as its research subject. By integrating statistical methods and algorithms, such as magnitude-based decision and machine learning, this study explores the impact of competition performance on match outcomes and constructs a predictive model. This study aims to build upon the research achievements of previous scholars and provide a theoretical foundation for coaching practices and enhancing players' match performance by examining the significance of various dimensions of competition performance in influencing match outcomes.

2 Materials and methods

2.1 Sample

This study involved the analysis of publicly available data obtained from the post-match analysis reports published by the FIFA Training Center (https://www.fifatrainingcentre.com), and the reliability and accuracy of the data sources in the reports have been validated (20, 21). The total includes 94 indicators related to performance in the competition. Considering the significant difference in data between overtime matches and regular time matches, five matches that entered overtime in the knockout stages were excluded, and the remaining 118 sets of data from 59 matches were analyzed and studied. The dependent variable was the match outcome, and the independent variables were in possession, out of possession, and running-related indicators.

2.2 Statistical analyses

2.2.1 Data pre-processing

The possession phase, out of possession phase, and running-related indicators were standardized according to the possession rate of both sides in the match. Among them, the data obtained when the team of interest had possession were standardized to the value corresponding to the team's 50% possession rate:

$$V_{\text{standardized}} = \frac{V_{\text{original}}}{P_{\text{own}}} \times 50\% \tag{1}$$

Further, the data obtained when the opponent had the possession were standardized to the value when the opponent had a possession rate of 50%:

$$V_{\text{standardized}} = \frac{V_{\text{original}}}{P_{\text{opponent}}} \times 50\% \tag{2}$$

Indicators measured in percentages, such as ball possession rate, shooting accuracy rate, and success rate, were not standardized. Subsequently, nonclinical magnitude-based decision was used to statistically infer the standardized and reciprocal indicators under different game outcomes. Differences in means were converted into effect sizes (ES), and the inferred results were presented as ES ± 90% CI. According to the magnitude of the ES, the ES thresholds for small, moderate, large, very large, and extremely large were 0.2, 0.6, 1.2, 2.0, and 4.0, respectively (22). When the 90% CI for the ES value does not include ±0.2, the difference can be considered pronounced.

2.2.2 Machine learning

Building upon previous research, this study selects several commonly used supervised learning algorithm models in team performance analysis, including DT, Logistic Regression (LR), SVM, AdaBoost, RF, and Artificial Neural Network (ANN) to construct predictive models for match outcomes. These models have their own characteristics and advantages, suitable for different types of data and problems. DT, LR and SVM are widely used supervised learning algorithms in scientific research, such as, predicting match outcomes, a team's goal difference, and players' physical performance (16, 23–25). AdaBoost and RF are both powerful ensemble learning algorithms widely used in competition performance and spatiotemporal player tracking dataset to predict outcomes or in-game status for their robustness and high predictive performance (24, 26). It reduces the risk of overfitting and enhances the model's accuracy and robustness. ANN is a computational deep learning model inspired by the human brain's neural networks. It can learn complex patterns and relationships in data by adjusting the weights of the connections based on the error in predictions (27, 28). The dataset was split into training ($n = 106$) and validation ($n = 12$) sets while utilizing the 10-fold cross-validation to avoid overfitting the training data (29). The commonly used methods for hyperparameter tuning include Bayesian optimization, random search, and grid search. In this study, grid search was chosen for hyperparameter tuning to automatically select the optimal parameter combination and iterate through the process. The model's evaluation involves the calculation of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) to compute the model's Accuracy (Acc), Precision (P), Recall (R), Specificity (S), and F1 score, as shown in the following formulas:

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

$$P = \frac{TP}{TP + FP} \tag{4}$$

$$R = \frac{TP}{TP + FN} \tag{5}$$

$$S = \frac{TN}{TN + FP} \tag{6}$$

$$F1 = \frac{2PR}{P + R} \tag{7}$$

TP: number of samples predicted as true and their actual values were true, FP: number of samples classified as true but their actual values were false, TN: number of samples classified as false but their actual values were true; FN: number of samples classified as false and their actual values were false (12, 30). Besides The area under the receiver operating characteristic curve (AUC) was calculated to assess the predictive performance of the model. Accuracy, AUC, Recall, Specificity and F1 score explain the predictive performance as follows: 0.5 (meaningless), 0.51–0.69 (poor), 0.7–0.79 (fair), 0.8–0.89 (good), 0.9–0.99 (excellent), 1 (perfect) (31, 32). Considering the role of SHAP values in explaining feature importance, this study selects the model with the highest goodness of fit to calculate SHAP values and analyze their importance on match outcomes (33).

Initially, the raw indicators were standardized, and the effect size for magnitude-based decision was calculated for indicator selection using the Microsoft Excel spreadsheet specially designed by Hopkins (34). Machine learning algorithm models were constructed and competition performance features were analyzed using the Scikit-learn library in Python 3.8.

3 Results

Magnitude-based decision was utilized to calculate the effect sizes (ES) and confidence intervals of the standardized indicators, concentrating on those metrics that are most likely to impact competition outcomes. The ES values and confidence intervals for the possession phase, non-possession phase, and running-related indicators are presented in Figures 1–3. Fourteen indicators were selected based on the magnitude of their inferred impact on match performance.

Table 1 shows the selected input indicators for model construction whereas the outputs were the competition outcomes. The classification of competition outcomes consists of two categories: winning and non-winning, where draws and losses are included in the non-winning category. "Winning" is assigned a value of "0", and "non-winning" is assigned a value of

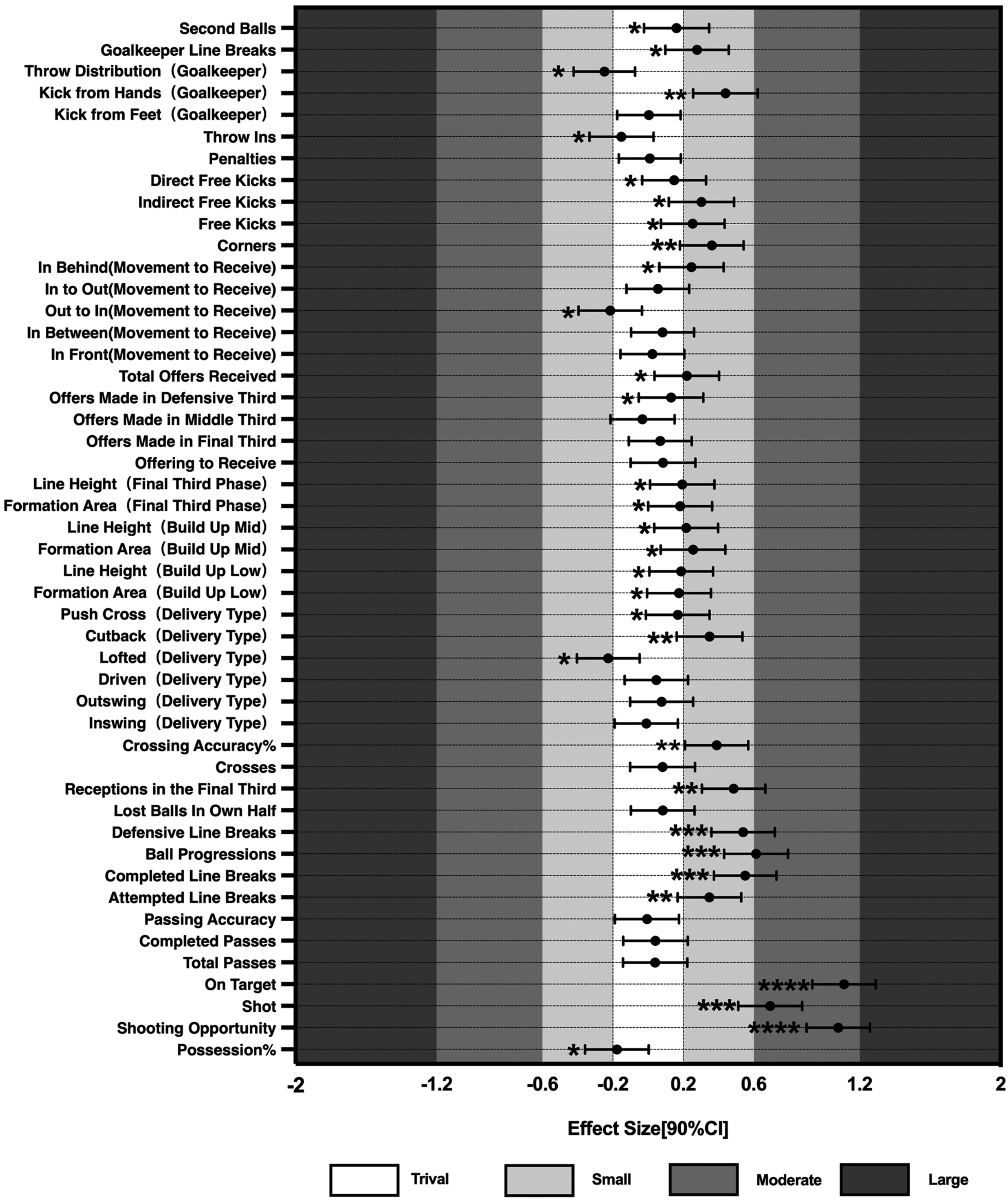

FIGURE 1
Comparative results of technical and tactical performances in possession phase. When the bars of one variable crossed the negative and positive smallest worthwhile change threshold at the same time, the effect was unclear. Asterisks indicate the likelihood for the magnitude of the true differences between mean as follows: *possible; **likely; ***very likely; ****most likely.

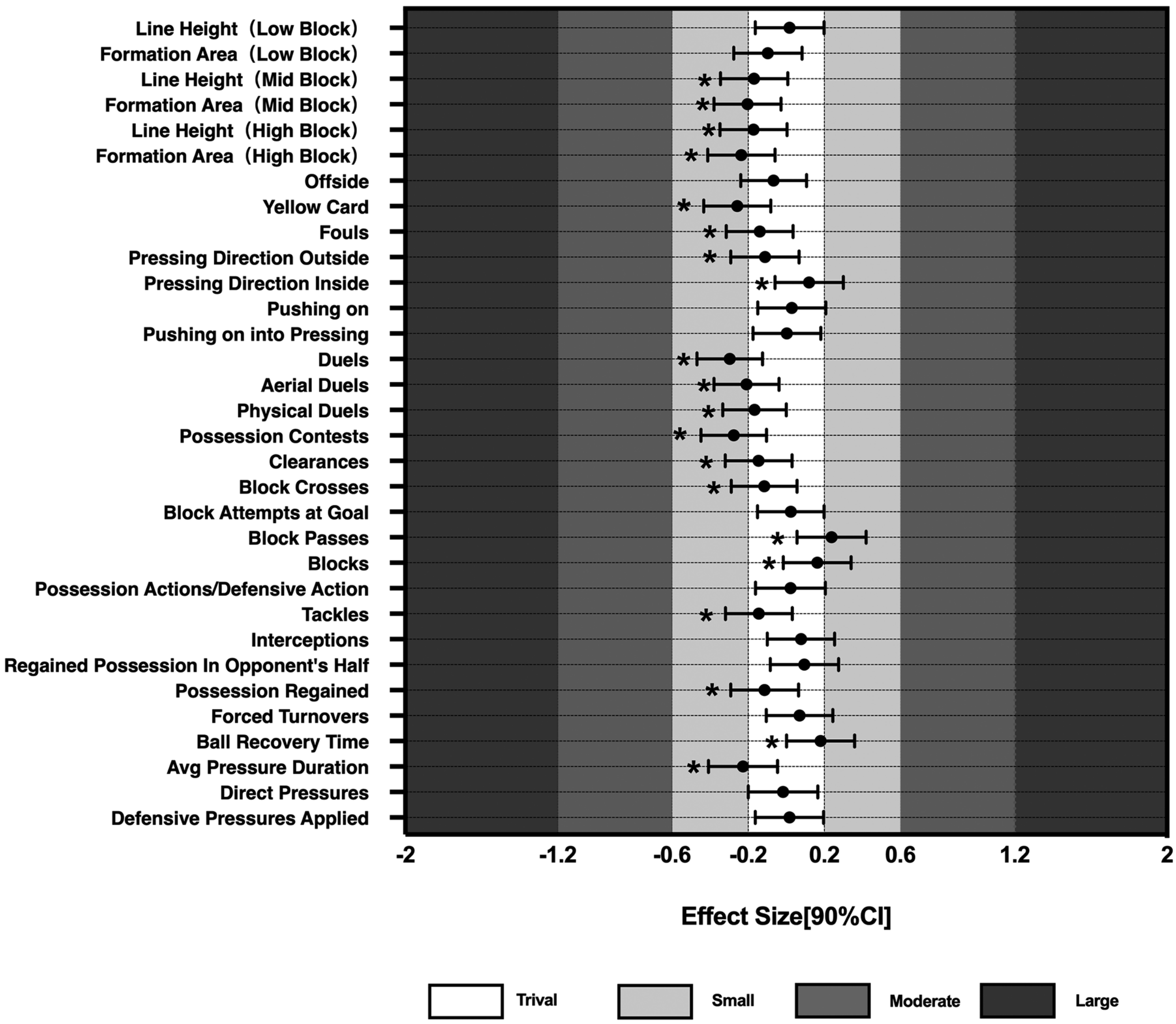

FIGURE 2
Comparative results of technical and tactical performances in the non-possession phase. When the bars of one variable crossed the negative and positive smallest worthwhile change threshold at the same time, the effect was unclear. Asterisks indicate the likelihood for the magnitude of the true differences between mean as follows: *possible; **likely; ***very likely; ****most likely.

"1" as the output of the model. Using six different machine learning algorithms to construct a model for predicting competition outcomes, the predictive performances of the different models are shown in Table 2. The confusion matrices of the six models—DT, LR, SVM, RF, AdaBoost, and ANN—are shown separately in Figure 4. By evaluating the accuracy of the predictive models, it is observed that ANN (75.42%) = LR (75.42%) > SVM (72.88%) = RF (72.88%) > AdaBoost (70.34%) > DT (67.82%). However, the AUC value of the ANN model (76.96%) exceeds that of the LR model (74.86%). Overall, the performance of the ANN model is superior in predicting match outcomes.

SHAP values were then utilized to assess the significance of indicators in the ANN model designed for forecasting match outcomes. The importance ranking of the 14 features is shown in Figure 5. SHAP values are on the *x*-axis, indicating the impact of an indicator on the model's output. A positive SHAP value indicates that the feature increases the predicted value, while a negative SHAP value indicates that it decreases the predicted value. The color represents the indicator value; blue dots indicate low significance of the indicators, while pink dots indicate high significance of the indicators.

4 Discussion

This study developed a predictive model for match outcomes using performance data from the Qatar World Cup, with the Artificial Neural Network (ANN) model exhibiting the highest predictive performance (Accuracy = 75.42%; AUC = 76.96%;

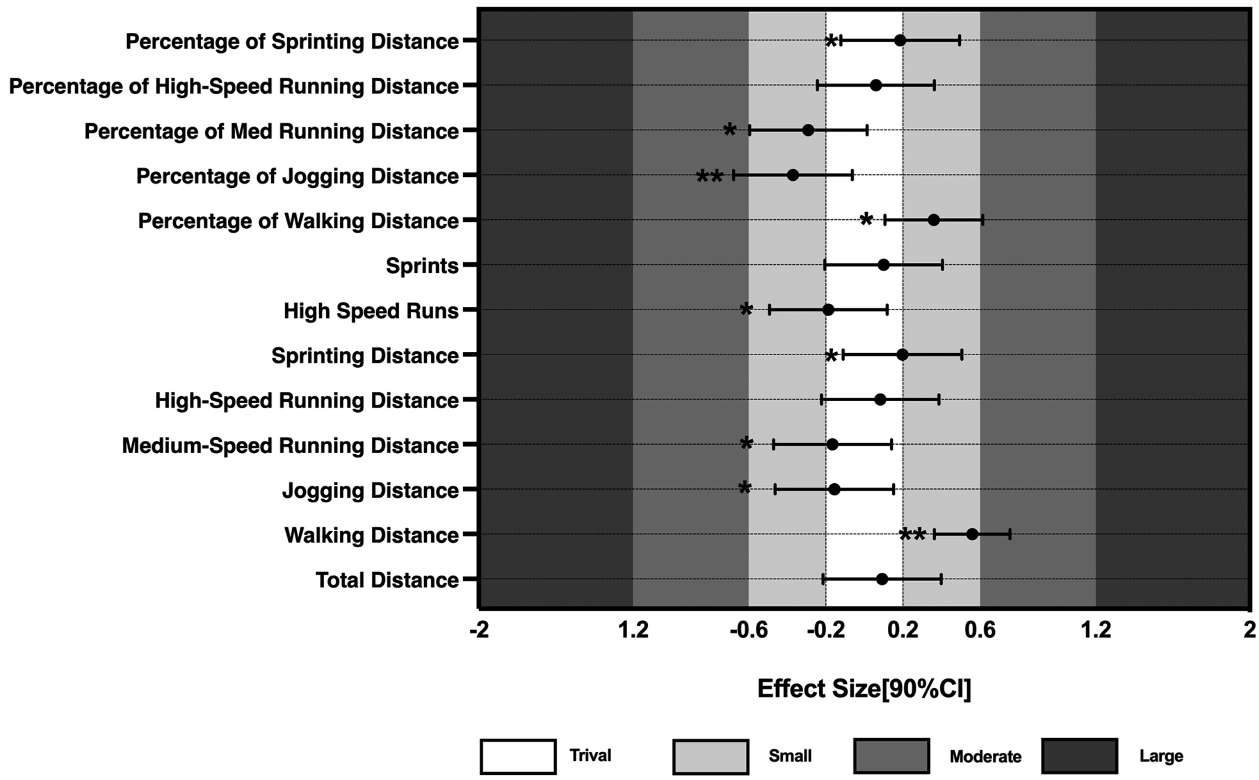

FIGURE 3
Comparative results of running-related performance. When the bars of one variable crossed the negative and positive smallest worthwhile change threshold at the same time, the effect was unclear. Asterisks indicate the likelihood for the magnitude of the true differences between mean as follows: *possible; **likely; ***very likely; ****most likely.

TABLE 1 Selected indicators.

Categories	Input indicators
In possession	On Target, Shooting Opportunity, Shot, Ball Progressions, Completed Line Breaks, Defensive Line Breaks, Receptions in the Final Third, Kick from Hands (Goalkeeper), Crossing Accuracy %, Cutback (Delivery Type), Corners, Attempted Line Breaks
Running-related	Walking distance, Percentage of Jogging Distance

Precision = 72.73%; Recall = 65.31%; Specificity = 77.03%; F1 score = 68.82%). Fourteen indicators were incorporated into the model construction, with their importance ranked as follows: On Target, Shooting Opportunity, Ball Progressions, Kick from Hands (Goalkeeper), Percentage of Jogging Distance, Completed Line Breaks, Corners, Crossing Accuracy%, Receptions in the Final Third, Shot, Attempted Line Breaks, Walking Distance, Defensive Line Breaks, and Cutback (Delivery Type).

Machine learning algorithms have been extensively applied in the realm of team sports. In this study, the ANN model demonstrated superior performance. ANN models are highly effective in capturing non-linear relationships and feature interactions due to their multi-layered architecture. Nonetheless, the Logistic Regression (LR) model achieved a comparable accuracy (75.42%) to that of the ANN model. The linear relationship between competition performance and outcomes may explain why the LR model exhibits strong performance. LR, being a simpler model, is less prone to overfitting compared to ANN, particularly when the dataset is not exceedingly large. Additionally, hyperparameter tuning during model construction can effectively enhance the performance of the LR model. The robustness of the ANN model is reflected in its high precision (72.73%) and specificity (77.03%), indicating its ability to accurately identify non-winning matches. This suggests that the ANN model effectively distinguishes between winning and non-winning conditions, likely due to its ability to process and learn from detailed and varied input indicators (35). In complex scenarios, technical and tactical performance significantly impacts competition outcomes. Therefore, the objective and reliable match outcome prediction provided by the ANN model is more suitable for meeting the analytical needs of match performance than solely relying on expert experience, intuition, or basic statistical data.

From the perspective of predictive performance, our findings exhibit a degree of comparability with previous studies. Some scholars have used the ANN model to predict the outcomes of the 2006 World Cup, achieving an accuracy rate of 76.9%, which is slightly higher than the accuracy rate observed in this study (36). One reason for this difference is that in this study, draws and losses are categorized as non-winning matches, affecting the distribution of the game outcomes dataset. Additionally, the

TABLE 2 Model performance Evaluation.

Model	Accuracy	AUC	Precision	Recall	Specificity	F1 score
DT	67.82%	66.84%	61.22%	61.22%	72.46%	61.22%
LR	75.42%	74.86%	70.83%	69.39%	78.51%	70.10%
SVM	72.88%	78.62%	77.42%	48.98%	71.26%	60.00%
RF	72.88%	74.18%	65.31%	68.09%	76.06%	66.67%
AdaBoost	70.34%	69.65%	64.00%	65.31%	75.00%	64.65%
ANN	75.42%	76.96%	72.73%	65.31%	77.03%	68.82%

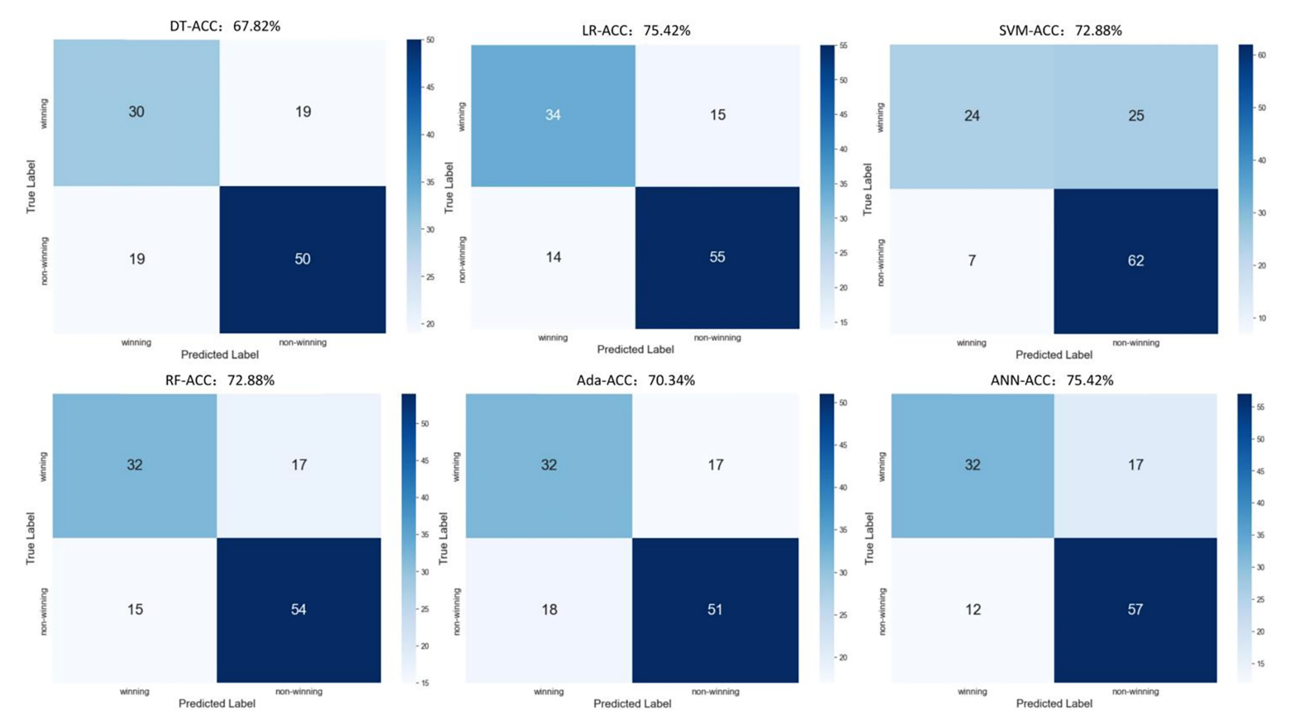

FIGURE 4
Model confusion matrix.

increasing complexity of football matches challenges the predictability of match outcomes (37). When using ANN and LR to build models, the prediction accuracy was 75.04% (38). Using ANN to construct a predictive model for the outcomes of the 2018 World Cup, the model successfully predicted the team's outcomes as either loss or win 72.7% and 83.3% of the time, respectively (39). Furthermore, utilizing MBD for screening performance indicators in competitive settings results in superior predictive performance of alternative algorithmic models compared to previous research (40, 41).

SHAP analysis revealed that the most influential indicators in the ANN model were "On Target", "Shooting Opportunity", and "Ball Progressions". These indicators significantly contributed to the model's predictive accuracy, underscoring their critical role in determining match outcomes. The high SHAP values suggest that frequent occurrences of shots on target and shooting opportunities are strong predictors of match victories. Similarly, effective ball progressions are crucial for creating scoring opportunities, thereby increasing the likelihood of winning. Research has shown that shooting-related indicators, such as the number of shots and shots on target, significantly influence outcomes in various football leagues, including the UEFA Champions League, English Premier League, La Liga, and CSL (42–44). Moreover, these indicators play a crucial role in determining match outcomes under various contexts (45, 46). However, "Shots" exhibit negative SHAP values for higher feature values, indicating a detrimental effect on the model's output. This suggests that winning a match depends more on the quality of shots rather than the quantity (44, 47). In this World Cup, the total number of shots is not the main factor in determining match outcomes; rather, an increase in shots on target improves the probability of winning.

Ball Progressions refer to a player's ability to penetrate the opponent's defensive space through dribbling, thereby disrupting their defensive formation. This concept integrates the player's actions and the defensive strategies employed by the opposing team, thereby granting it spatial attributes for practical implementation. Defenders typically mark their opponents as a

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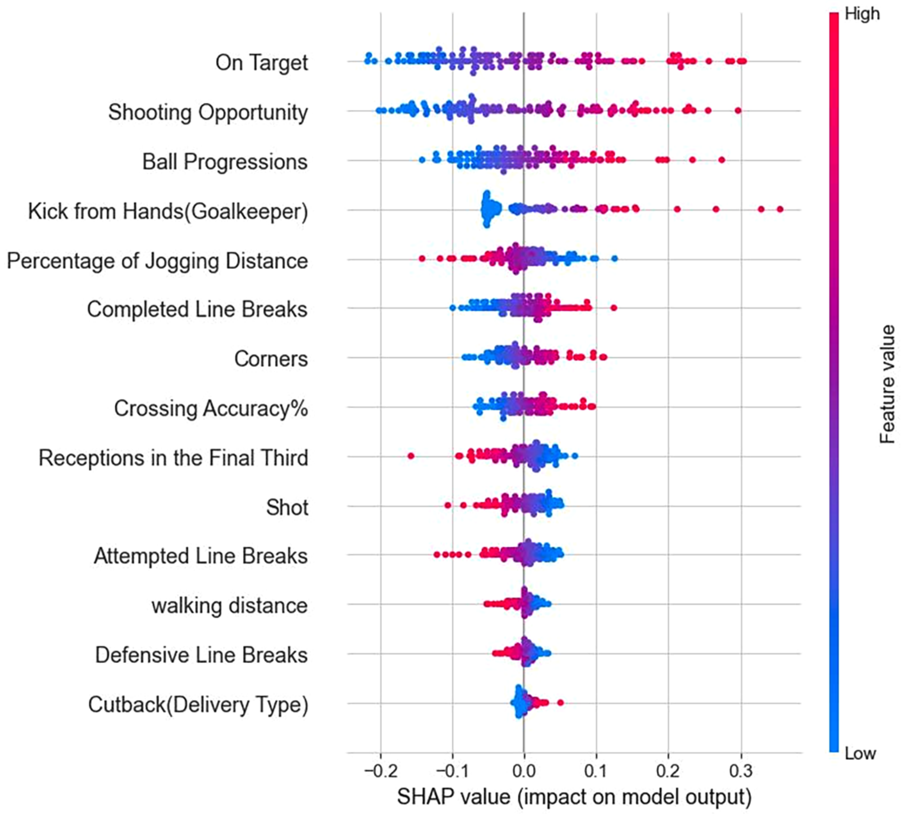

FIGURE 5
SHAP value ranks.

defensive method, whereas advancing the ball allows for the penetration of the opponent's defensive territory, creating numerical imbalances and scoring opportunities (48). Completed Line Breaks, Attempted Line Breaks, and Defensive Line Breaks are crucial indicators for predicting match outcomes. Line breaks refer to an attacking player dribbling or passing the ball through the lowest-positioned player in the opponent's defensive line. By counting the number of times the opponent's defensive line is penetrated, the team's attacking style and sequence can be quantified.

In this study, SHAP values revealed that an increase in the number of Receptions in the Final Third decreases the model's predictive accuracy, indicating that winning teams in this tournament were more efficient in their offensive strategies. High values of Corners, Crossing Accuracy%, and Cutback (Delivery Type) enhance the model's predictive accuracy, reflecting that winning teams favor a more direct offensive approach. The importance of corners on match outcomes has been confirmed in major European leagues and in the FIFA Men's and Women's World Cups (49–51). In the 2022 World Cup, 45 goals resulted from crosses, whereas in the 2018 World Cup, only 25 goals were scored from crosses. Dense defense in the middle forces teams to utilize the space on the flanks and create shooting opportunities through crosses. Therefore, winning teams are more efficient in converting crosses into goals than non-winning teams. Research has analyzed the winning factors in the English Premier League, La Liga, and Major League Soccer, finding that crossing is the most crucial passing method in games (12). Teams that are weaker or trailing in score often tend to focus on crossing tactics (52).

SHAP values indicate that Kick from Hands also positively impacts game outcomes. Previous studies emphasized the defensive role of goalkeepers, noting that 21% of their actions focused on controlling space and maintaining possession, while creating scoring opportunities accounted for only about 3% (53). Recent research has found that goalkeepers' roles in attacking have increased, accounting for more than 75%–80% of their actions, and the quality of their attacks has improved, with a success rate ranging from 88.97% to 91.66% (54). The match philosophies of various countries have unanimously emphasized the importance of transitioning from attack to defense and vice versa. The significance of goalkeepers' kicks from hands in winning games has confirmed this viewpoint: goalkeepers can be the starting point for transitioning from defense to attack.

This study found no significant differences in high-intensity technical and tactical behaviors between winning and losing teams in the 2022 World Cup. Running indicators, such as high-speed running and sprinting, are no longer effective in predicting match outcomes (55). The percentage of running speeds below 15 km/h and the distance covered at walking were higher in losing teams compared to winning teams. Therefore, it is speculated that the players of the winning team performed better in terms of recovery and the associated lactate clearance after high-intensity exercise (56). Despite the comparable amount of high-intensity activities between winning and losing teams, the potentially slower recovery and running speed of players in the losing teams might predispose them to make more mistakes during the offensive and defensive transition phases. Further studies in this regard to identify the underlying reasons are warranted.

In conclusion, this study developed a predictive model for the outcomes of the Qatar World Cup utilizing the ANN algorithm. It explores the key indicators influencing the outcomes of the Qatar World Cup and summarizes the performance characteristics of both winning and non-winning teams. This provides a theoretical basis for assessing the feasibility of using the ANN algorithm to predict World Cup outcomes.

5 Conclusion

The current research findings demonstrate that the ANN model is capable of predicting the outcomes of Qatar World Cup matches with good accuracy. Furthermore, an analysis of the indicators influencing match outcomes was conducted using SHAP values. The most important indicators affecting match outcomes are On Target and Shooting Opportunity, rather than the number of shots. This suggests that in training, more emphasis should be placed on improving the quality of shots and creating shooting space. Ball Progressions and Line Breaks also significantly impact winning matches, and effective attacks should attempt to penetrate the opponent's defense. Crosses and Corners remain crucial offensive tactics for winning teams, and coaches should arrange targeted offensive and defensive training sessions. Winning teams display lower percentages of Jogging Distance and shorter Walking Distances. Additionally, this study found that goalkeepers' long kicks are a significant method of attack for teams. Therefore, coaches should focus on the sensitive indicators mentioned above during training and arrange sessions accordingly.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

YS: Writing – original draft, Writing – review & editing. GS: Writing – review & editing. CW: Investigation, Writing – review & editing. BP: Investigation, Writing – review & editing. WZ: Investigation, Writing – review & editing. RZ: Investigation, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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Cognition in elite soccer players: a general model

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This paper presents a general model of the cognitive processes involved in each play situation of soccer at the elite level. Theoretically the model draws on general frameworks from cognitive psychology and neuroscience, in particular the affordance competition hypothesis and the reward prediction error theory. The model includes three functional stages: situational assessment, action selection and execution, and outcome assessment. The three stages form a perception-action cycle that corresponds to a single play situation. The cognitive processes operating at each functional stage are described and related to soccer research by a review of 52 empirical studies. The review covers the main cognitive processes that have been studied in soccer research: visual orientation and attention, pattern recognition, anticipation, working memory, action selection and decision making, executive control processes, as well as behavioral and cognitive learning. The model accommodates the wide variety of findings in the empirical literature and provides a general organizing frame for cognitive soccer research at the elite level. The influence of emotional and stress-related factors on cognition are also discussed. Four general limitations of the existing soccer research are identified, and suggestions for future studies include development of more naturalistic and interventional study designs. By specifying the different cognitive processes in soccer and their dynamic interactions the model has many applied perspectives for soccer training at the professional level. Overall, the paper presents the first integrated process model of cognition in elite soccer players with implications for both research and practice.

KEYWORDS

soccer (football), cognition, perception-action cycle, model, review

1 Introduction

Soccer is the most popular sport in the world: hundreds of millions play the game at amateur level, and even more follow professional teams as they compete in national leagues and international tournaments. In this multi-billion dollar industry soccer clubs devote enormous resources to optimize the performance of their players. The efforts have traditionally focused on tactical, technical, and physiological efficiency, but there is a growing area of research investigating cognitive processes involved in elite soccer performance (Scharfen and Memmert, 2019). This interest is well motivated given the nature of the game. Soccer players perform in a fast-paced, dynamically changing environment, where the simultaneous actions of many opponents and teammates must be rapidly perceived and predicted in order to respond effectively at any given moment. This challenging task engages a wide variety of cognitive processes such as visual perception, attention, anticipation, working memory, social cognition, and executive control, which must work flexibly together to sustain the player's actions.

In the last two decades many aspects of cognition in soccer have been investigated empirically, as detailed later in this paper. The studies have employed a mixture of general cognitive testing and soccer-related experimental tasks, typically contrasting the performance of elite and less skilled players, and in some cases correlating these measures to performance on the pitch. Many interesting findings have been made, but studies have typically focused on isolated aspects of cognition without reference to a general theoretical framework. Broader theoretical conceptualizations of cognition in soccer have been put forward, in particular relating to the decision making aspect (Petiot et al., 2021; Raab, 2012). However so far no theory has encompassed the full spectrum of cognitive processes involved in soccer. Given the complexity of cognitive mechanisms that are involved in soccer, especially their dynamic interactions, an integrative process model could have large utility for the field. The holistic perspective provided by such a model could also guide future research by pointing to aspects of cognition in soccer that have not received empirical investigation so far. Not least, from a practical point of view, a detailed analytical framework could be highly useful to devise targeted cognitive training for soccer players and to open the possibility for cognition-based talent identification.

In this article we present a general model of cognitive processes in elite soccer players and review how the model relates to the current empirical evidence. The focus on soccer at the elite level is in line with most research in the field, and also reflects the fact that cognitive processes may be qualitatively different between novices and elite athletes, for example with respect to automaticity and the involvement of conscious thinking (Starkes et al., 2004). We discuss strengths and limitations of the model, offer a critical assessment of the empirical research in the field and, based on this, suggest new directions for scientific investigations of cognitive processes in elite soccer. We also outline applied perspectives of the model in relation to professional soccer training.

2 A model of cognitive processes in elite soccer

2.1 General principles of the model

The model depicted in Figure 1 describes the relation between the cognitive processes involved in each individual play situation of soccer at the elite level. The model describes the basic situational unit in the form of a single perception-action cycle. We define the basic situational unit as the events related to a single tactical action in soccer. If the player possesses the ball, an action may be a pass, a shot at the goal, or a dribble. If the player does not possess the ball, an action can be an attempt to tackle, to block the ball or the running course of an opponent player, or to move into a different part of the playing field for defensive or attacking purposes. The model applies both to situations with and without ball possession, where the latter is far more frequent. The typical duration of a single play situation is a few seconds, which allows for some perceptual updating and response preparation within the situation. Thus, the concept of an individual play situation and its corresponding action is defined at the tactical level, which is a more complex type of behavior than individual movements (see Schmidt and Lee, 2019, for research on the latter type of processes).

The model describes the cognitive processes during the play situation at different levels of analysis. At the most general level, the model describes how the player goes through three functional stages from start to end of the cycle: (a) assessment of the current play situation, (b) action selection and execution, and (c) assessment of outcome and systemic feedback. The model works in a cascading way, so earlier stages continue to be active during the processing at later stages and can influence these until an action has been fully executed. This way, Stage 1 continues to deliver information about the current play situation during the processes at Stage 2, which can for example lead to inhibition of an action if circumstances change midway. There

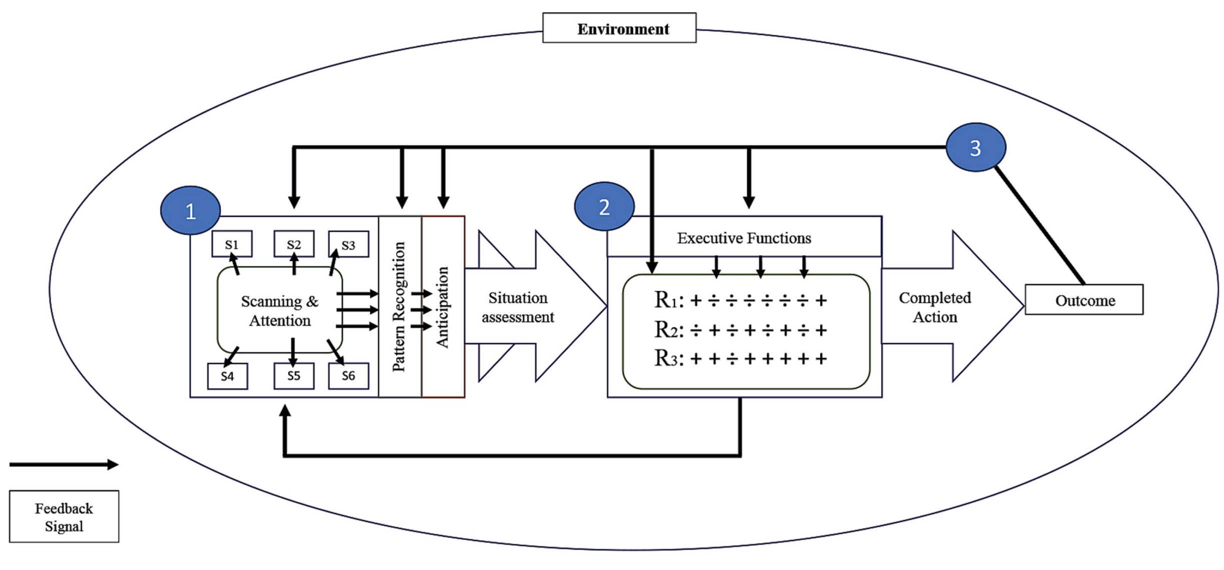

FIGURE 1
The three stages of a perception-action cycle in soccer. Stage 1, assessment of the current play situation; Stage 2, action selection and execution; Stage 3, assessment of outcome and systemic feedback. S$_{1-6}$, surrounding stimuli; R$_{1-3}$, competing response options. Plusses and minuses indicate excitatory and inhibitory influences on response selection.

are also feedback connections between Stage 2 and 1, so the process of action selection can initiate new exploratory behavior before an action is decided upon and fully executed. Several of the processes within stages also occur in parallel, for example the selection between response options at Stage 2. Therefore, although the model as a whole has a serial processing character, it encompasses parallel and interactive processes both within and between the three stages. Each functional stage depends on specific cognitive processes, as described in the following sections.

2.2 The three stages of a perception-action cycle in elite soccer

2.2.1 Stage 1

The function of the first stage is to provide the player with a continuous assessment of the current play situation. This mainly depends on visual perception, but also on other sensory modalities such as audition, somatosensation and proprioception. The perceptual processes are intimately connected to attentional functions, which direct focus toward particular aspects of the situation. The attentional focus is supported and elaborated by active exploratory movements, in particular visual orienting, and relies heavily on previous learning. Much of the orienting processes occur at an automatic cognitive level, but conscious intentions can also influence the player's behavior via executive control processes. Soccer-specific pattern recognition, for example of particular configurations of the surrounding players in relation to the ball, is also a central aspect of this stage. In addition, anticipations of the actions of other players are an integral part of the situation assessment, for example based on the postural positions of teammates and opponents. The outcome of Stage 1 is a dynamically updated assessment of the current play situation, including anticipations of the immediate future, which is represented in the player's working memory.

2.2.2 Stage 2

The function of the second stage is to evaluate the currently relevant response options in order to select and execute a particular action. The response options are heavily narrowed down by the situational assessment from Stage 1, which activates only a few responses in the player's procedural long-term memory. The response options are simultaneously activated in specific neural populations within motor-related areas of the brain and compete for action selection. The activation of response options is not purely cerebral, but also have effects in the body in the form of muscle activations and preliminary movements. For a defensive player holding the ball, the relevant alternatives could for example be to pass the ball back to the goal keeper, to direct a long pass to a teammate further up the field, or to make a short pass to a fellow defensive player. Due to the speed of the game the selection and execution of actions largely occurs at an automatic, non-conscious level. The activation of specific response options depends on previous learning, which in the case of elite players amounts to thousands of hours of systematic training in specific play situations. By way of priming mechanisms, the response activations are also influenced by recent events in the game, for example following a successful encounter with an opponent player or a missed shot at the goal. The action selection is determined by an implicit evaluation of the potential risks and benefits related to each potential action, which also includes the probability of carrying the action out as intended. The evaluation is implicit in the sense that it depends on excitatory and inhibitory activity (formed by previous learning) in neural networks representing the competing responses, rather than a conscious deliberation of choice options. The level of risk-taking in the decision process depends on personal characteristics of the player, including the current level of self-confidence, as well as the overall game situation. While the action selection process itself is essentially non-conscious, executive processes can influence the outcome for example by representing team strategy and other conscious intentions. The automaticity of the response selection varies both between situations and individuals. A player may be trained to systematically carry out a specific action in a particular situation, but can also be trained (or personally inclined) to act in a more flexible or creative manner. A largely automatic response mode corresponds to a strong activation of just one response in Stage 2, whereas a more flexible response mode entails significant competition between several response options and typically more feedback interaction with the information gathering processes of Stage 1. In any case, the outcome of Stage 2 is the full execution of a particular action. The action implies an expectation of its likely outcome, based on previous learning, which feeds into the next stage of the perception-action cycle.

2.2.3 Stage 3

After the action has been carried out the player perceives the outcome. The perception of the outcome is directly coupled to the player's intention for the action and implies an assessment of its successfulness. The assessment activates the brain's reward systems and makes the player either more or less likely to repeat the same action in similar future situations. The degree of behavioral modification depends on the difference between the expected and actual outcome of the action, so large discrepancies (reward prediction errors) will lead to more changes. Specifically, the feedback is implemented via modifications of the cognitive and neural settings that are involved in Stages 1 and 2, for example leading to changes in the orientation behavior at Stage 1 or different response tendencies at Stage 2. This way, Stage 3 feeds back into new cycles of perception and action, provides opportunities for learning, and modifies the perceptual processing, decision making, and motor execution in future play situations.

3 Empirical research on cognitive processes in soccer

Empirical research on cognitive processes in soccer was pioneered in the 1990s (Williams et al., 1994; Williams and Davids, 1998) and has developed much during the first two decades of the 21st century. In this section we present a narrative review of this research field, theoretically organized by the functional categories and cognitive processes described in our model. In each subsection we describe the main empirical findings related to the cognitive process in question, discuss methodological and conceptual issues, and give an assessment of the current state of the evidence. The studies included in the narrative review were selected by the following criteria: they should report on empirical investigations of cognitive processes in soccer, include elite or highly experienced players, and be published in English language peer-reviewed scientific journals in 2003 or later.

Studies were not included if the investigation was mainly focused on clinical issues (e.g., concussion) or stress/fatigue, or if other sports were the main focus of the investigation. To avoid the added complexity of developmental processes, studies were also not included if participants were on average under the age of 18. The studies were found through searches in Web of Science by combinations of selected key words (e.g.: "soccer" or" football" and "cognition," "scanning," "anticipation," or "decision making") combined with exclusion criteria (e.g.: "not concussion," "not injury," and "not youth"). This was followed by screening of abstracts and final evaluation of the content of the studies. Additional studies were found through references in the selected articles. In total, 52 empirical studies are included in the narrative review. In addition, a number of more broadly focused theoretical and empirical papers are included to provide general context and background for the different subsections.

3.1 Stage 1: assessment of the current play situation

3.1.1 Visual orientation and attention

Soccer is a highly dynamic sport and to perform effectively players must continuously update their perception of the current situation. The most important source of perceptual information in soccer is vision, and relevant visual stimuli typically surround the player in all directions. Therefore effective orientation behavior in the form of eye movements, head turns, and whole body movements is presumably crucial to perform well. For this reason, and perhaps also because orientation behavior is readily observable, this has been one of the most active areas of investigation within cognitive soccer research, as well as in other sport disciplines (Klostermann and Moeinirad, 2020; Silva et al., 2022). It is also an area of high interest to coaches (Pulling et al., 2018). Orientation behavior is intimately linked to attentional functions, which guide exploratory movements to ensure that the most relevant information is focused on and perceived. In soccer visual attention is typically directed at the ball, the positions of opponents and teammates, open and closed spaces on the field, or postural cues for anticipating the actions of other players. General attentional priorities such as these guide the player's orientation behavior, but how they are weighted is often determined by specific events that occur during the visual exploration. This way, the relation between orientation behavior and attention is highly interactive. Conscious intentions, for example specific instructions by the coach, may also influence orienting behavior by way of executive control processes; however this top-down aspect has not been addressed directly in the empirical literature.

The large majority of studies on visual orientation behavior in soccer has focused on eye movement patterns (McGuckian et al., 2018b). The empirical findings in this research field are mixed, and there seems to be no general difference between elite and amateur players with regard to the frequency of eye movements and the duration of fixations. For example, Cañal-Bruland et al. (2011) found that expert soccer players made fewer fixations of longer duration than controls when looking at images of play situations, whereas Roca et al. (2011) found the opposite pattern. Rather than showing general characteristics of eye movements in skilled players, many studies suggest that a number of variables modify scanning rates and fixation patterns in different play situations. A commonly studied situation is ball reception, often in connection with subsequent passing. Natsuhara et al. (2020); see also Oppici et al. (2017) studied how soccer players reacted to life-sized videos of real play scenes, where a physical ball was ejected toward the participant according to the play situation. This was done to simulate ball reception and passing decisions. Natsuhara et al. (2020) found that skilled players fixated more than controls on opponents before receiving, and more on non-marked attackers and the team-mate to receive the pass before passing. This suggests that skilled players search the visual surroundings for more relevant information than controls, flexibly adapted to the current play situation. Similar findings have been made in studies of visual orientation behavior as a function of the player's distance to the ball. Roca et al. (2013) found that skilled players typically made shorter and more numerous fixations when the ball was far away, presumably to perceive the general pattern of play. On the other hand, when the ball was close, skilled players made fewer fixations of longer duration and focused mainly on postural cues of the player in ball possession, presumably to predict the next movement. In contrast, less skilled players tended to focus directly on the ball in both types of situations, indicating a lack of dynamic adaptation of their visual exploration behavior.

Another line of studies has focused on the influence of individual characteristics. Roca et al. (2018) investigated how individual differences in creativity are related to visual search strategies. In this study, participants were presented with life-sized video simulations of attacking situations while in ball possession. The most creative players (i.e., those who created more flexible and original decisions) differed in visual search strategy by making more short fixations of informative locations. Roca et al. interpreted this as reflecting a broader attentional focus in creative players. Individual differences in working memory capacity (see also Section 3.1.4) might also be relevant for visual orientation behavior. However, Harris et al. (2020) found that gaze strategy did not differ between two groups of athletes (where one group included soccer players) with different working memory capacity, as measured by multiple object tracking (see also Cañal-Bruland et al., 2011).

Another important question concerns the type of stimuli that elite players typically attend to. This is often studied in relation to anticipation processes (see also Section 3.1.3). There is evidence that superior perceptual abilities in sports lead to better anticipation (Brams et al., 2019; Williams and Jackson, 2019) and that more skilled players, who tend to anticipate better, also employ a distinct visual search strategy. Whereas experts and novices alike will often fixate on the ball and the player in possession of it, which aligns with a primary reliance on postural cues, experts will do this significantly less (Casanova et al., 2013; Roca et al., 2011), indicating their superior integration of other sources of information. Indeed, when provided with contextual priors in the form of opponents' action tendencies, experts but not novices spend significantly more time watching other elements in the visual field than the player in possession of the ball (Gredin et al., 2018). Additionally, when the main action is far away, more skilled players will focus relatively less on the player in possession of the ball and more on other surrounding subjects (Roca et al., 2013). These results further highlight that elite soccer players incorporate multiple sources of information when anticipating and can adjust their strategy depending on the quality of available information.

Most research on visual orientation in soccer is laboratory-based, which does not necessarily generalize to real-life soccer play. Gaze patterns may be different for artificial, two-dimensional stimuli compared to immersion in real-life environments (Dicks et al., 2010; Foulsham et al., 2011), and virtual reality environments may also elicit different exploration behavior than natural situations (Pastel et al., 2021). To address this issue, a few recent studies have measured visual orientation behavior during real-life games and related it directly to performance on the pitch. McGuckian et al. (2018a) found that the frequency of head turns in live matches were related to faster passing response time. The study did not find a relation between orientation behavior and the success rate of the passes, but this has been demonstrated in more recent studies. Jordet et al. (2020); see also Phatak and Gruber (2019) studied orientation behavior in the form of head turns away from the ball, which they video recorded during 21 competitive matches in a group of players from the English Premier League. Jordet et al. (2020) found positional differences in scanning behavior: central midfielders and central defenders scanned more, and forwards least. They also found differences related to the game situation, for example with less scanning under tight opponent pressure or close to the opponent goal. Importantly, Jordet et al. (2020) found that the probability of making successful passes increased with scanning frequency. However the effects were not large, and the authors concluded that the frequency of scanning (head turns) seems to have only a small, yet positive role in elite players' performance. Based on videos of 72 professional players in live matches, Caso et al. (2023) studied head and body movements (Visual Exploratory Activities; VEAs) prior to receiving the ball. The players belonged to the same club, which used a 3-man passing system: the final pass would be directed at the player being measured, whereas the penultimate pass represented valuable early information for this player. Caso et al. (2023) found that the amount of VEAs in relation to the penultimate pass predicted the adequacy of the subsequent pass by the player. Caso et al. (2023) also found effects of playing position, where midfielders made more VEAs than defenders and attackers. Aksum et al. (2020) studied eye movements in 5 elite players during match play in the Norwegian premier league. Eye movement patterns varied with attacking-defending phases, as well as the complexity of the situation: fixations were longer when a higher number of "areas of interest" (e.g., ball, teammate, opponent) were present in the visual field, suggesting that longer processing time was needed when more information was available. Notably, Aksum et al. (2021) also found that scan times were significantly shorter in real-life play than typically reported for laboratory tasks, which questions the validity of such visual orientation studies in soccer. This finding is in line with the review of McGuckian et al. (2018b), who also found that eye movement patterns varied with the representativeness of the study design [see also Aksum et al. (2021)].

In summary, research has shown that visual orientation behavior and related attentional processes vary systematically with the play situation, as well as with individual player characteristics such as creativity. Skilled players tend to focus their attention on the most informative aspects of the situation, which can vary on several dimensions. Whereas the majority of studies in this field are laboratory-based, a few recent studies report on relations between real-life orientation behavior and game performance, especially passing, but this type of evidence is still limited. Another limitation of research on visual orientation and attention, which also applies to cognitive soccer research in general, is that studies typically focus on situations with ball possession or reception, but not the large majority of play situations where the player in not in immediate contact with the ball. Also, a lack of intervention studies makes it difficult to know if and how orientation behavior is causally related to higher performance, or merely correlated with it. The executive control aspect of orienting in soccer is neither addressed in current research. Thus, in spite of the relatively large research interest in this subfield, many questions remain unanswered.

3.1.2 Pattern recognition

There is no clear evidence that basic perceptual functions are superior in elite athletes (Ward and Williams, 2003), but specialized pattern recognition abilities have long been considered central for development of expertise (Chase and Simon, 1973). Studies of expertise in numerous fields have shown that highly specific knowledge structures that represent relations between individual items (e.g., "templates"; Gobet and Simon, 1996) develop after extensive practice in a particular domain. Williams et al. (2006) presented a method for studying pattern recognition in soccer by using point-like representations of play situations. For highly skilled players they found no difference in memory performance for video clips of play situations with these abstract displays and fully detailed videos, but for less skilled participants there was a significant degradation. This indicates that experts are better able to pick up abstract structural play configurations, whereas less skilled players rely on more superficial sensory features. In a follow-up study Williams et al. (2012) found that dynamical motion aspects of the patterns, not static configurations, differentiated soccer experts from lesser-skilled observers. They also found that relative, not absolute, motion patterns are crucial. Other studies have further investigated which features of a play configuration is typically focused on by soccer experts. One finding is that centrally located attacking players seem to be especially critical for experts (North et al., 2009). This was indicated by the number of eye movements directed at these players as well as by experimental removal of player stimuli, which shows that movements of central attacking players hold essential information (North et al., 2017). However the experimental testing in these studies was based on general views of the soccer field, whereas in actual play the most important features are likely to vary with the position and functional role of each player. Even for a given position, there are presumably a great variety of playing patterns that are relevant to expert performance in soccer. Apart from the few general principles of pattern recognition in soccer that have been uncovered so far, the detailed nature of these patterns has not been characterized empirically. In addition, the link between pattern recognition skills and actual soccer performance has not been established.

Another important aspect of pattern recognition is the relation to anticipatory processes. From a theoretical perspective pattern recognition should be highly relevant to anticipation, since the identification of familiar situations and knowledge of their usual outcomes can be used to predict events in the present (Navia et al., 2018). Moderate correlations between proficiencies in these two functions have been documented, and eye tracking data indicate visual search strategies that show both similarities and differences when performing anticipation tasks and recognition tasks (North et al., 2009). Also, participants tend to report on the basis of more sophisticated memory representations when anticipating than when recognizing (North et al., 2016). Thus, although there is likely some overlap between pattern recognition and anticipation, the processes appear to be functionally distinct and are represented separately in our model.

3.1.3 Anticipation

Interceptive strategic sports like soccer are defined by a fast-paced and dynamic environment in which actions must be executed quickly to take advantage of opportunities before they disappear. As such, the ability to predict future events and prepare actions ahead of their occurrence is advantageous (Navia et al., 2018). There are multiple definitions of anticipation in the sports literature, but for most soccer-related studies, anticipation is primarily conceptualized as the ability to predict the actions of other players, usually opponents (Zhao et al., 2022). Anticipations of the movements and future positions of objects in motion have also been investigated (Craig et al., 2009), but these studies make up only a fraction of the literature and will not be discussed here. Anticipation has been highlighted as a key factor in successful performance in many different team sports (Ashford et al., 2021), and research generally supports the notion that elite athletes in strategic sports possess superior anticipatory abilities within their domains of expertise (Petiot et al., 2021). In soccer, coaches from Brazil to Germany suggest its importance in different facets of decision making (Klatt et al., 2019).

In our model anticipation is considered a part of Stage 1 and relates to predictions about the actions of other players and the immediate development of the current play situation. Predictions about the consequences of one's own actions are regarded as part of Stage 2 in our model (see section 3.2). Likely based on more complex cognitive operations than simple perception, in particular advanced pattern recognition processes, anticipation serves to provide accurate predictions of how the situation might change in the next few seconds. Soccer-related anticipation studies can be classified depending on the kinds of information and cognitive strategies participants are thought to employ when performing tasks. Most studies assume that soccer players rely on postural cues to predict the actions of opponents. Indeed, skilled soccer players seem to possess a superior ability to quickly identify the direction of biological motion, not just for soccer-related motions, but also for more general kinds of human kinematics (Romeas and Faubert, 2015). Typically, anticipation studies require participants to watch a clip from a real soccer match in which an opposing player in possession of the ball is about to take an action. The clip is occluded before the action and participants must predict what the action is going to be. Actions are considered successfully anticipated if participants' predictions correspond to the action taken by the opponent in the clip. Generally, studies support the notion that skilled soccer-players outperform less skilled players on such postural tasks (Casanova et al., 2013; North et al., 2016; Roca et al., 2013, 2011). Many studies do not include measures of response time, but those that do generally show that more skilled players anticipate significantly quicker (Gredin et al., 2018). Further, more skilled soccer players are better at anticipating deceptive moves (Wright et al., 2013), at generating relevant action options for an opposing player (Belling et al., 2015), and at generating more verbal statements of higher complexity about their own thought processes during anticipation (Roca et al., 2013, 2011). At the neurophysiological level, these processes may be supported by mirror neuron systems (Gorgan Mohammadi and Ganjtabesh, 2024).

It seems clear that elite soccer players possess a superior ability to anticipate the actions of opponents, but they may utilize more than just postural cues to do so. Several studies supply participants with other helpful information such as the opponent's action tendencies or structural knowledge about players' positions on the field. Gredin et al. (2018) found that the provision of contextual priors through knowledge about opponents' action tendencies benefitted anticipation for both novice and expert soccer-players, but when opponents acted against their tendency, a detrimental effect was only observed for novices. This suggests that experts may be more skilled at determining when contextual information should be relied on or not. Similarly, Thomas et al. (2022) found that both skilled and less skilled players could covertly learn and benefit from opponents' action tendencies when anticipating, but when tendencies were suddenly switched, only skilled players adapted their expectations. Knowledge of the action tendencies of teammates is also important for anticipation, and developing this shared knowledge is a major focus in collective training sessions [see, e.g., Blaser and Seiler (2019)].

By varying the reliability of postural cues (by changing the time of clip-occlusion and the distance to the opposing player) and contextual information (by varying the consistency of action-tendencies), researchers have found that expert soccer players employ Bayesian probability-based strategies when anticipating (Gredin et al., 2021). Generally, skilled soccer players seem to possess a greater advantage in postural anticipation (North et al., 2016), and if postural cues are reliable, they will primarily base their anticipatory judgment on this source of information (Gredin et al., 2021). Further, though they may initially rely on contextual information, experts will switch to postural cues right before the opponent's action execution, when kinematic information is most reliable. A similar switch is not observed in novices (Gredin et al., 2018). However, when kinematic information is unreliable due to a greater distance from the action, early occlusion, or other kinds of image manipulation, contextual priors of both low and high reliability as well as structural information take precedence in anticipation (Gredin et al., 2018; North et al., 2016). Taken together, these findings show that expert soccer players utilize multiple different sources of information when anticipating, and that their superior performance may especially be due to an ability to adapt their anticipation strategy depending on the relative reliability of the different information sources.

As has been highlighted above, most studies make inter-group comparisons, showing differences in anticipation between groups of different skill levels. Very few studies, however, make intra-group comparisons between players at the same skill level. Because groups typically vary on several other variables than skill level such as years of experience, hours trained per week, playing position, and belief in own ability, it is difficult to determine if anticipation is linked directly to soccer performance or simply to greater familiarity with the game. Additionally it is difficult to determine to which extent anticipation is directly useful during soccer play or if more skilled players simply develop this ability without benefitting from it during matches. Intervention studies, in which anticipation processes are trained or experimentally manipulated, can potentially address this question, but limited research has been done in this area. In a review of video-based intervention studies of anticipation, Zhao et al. (2022) found that anticipation could be trained by such interventions. Additionally, in the single study that included transfer tests to soccer performance, anticipation improvements seemed to benefit performance (Gabbett and Mulvey, 2008). However, due to limited and conflicting findings on this question, it remains unclear how and to which extent anticipation is beneficial to actual soccer performance.

In a theoretical context, an additional issue can be raised regarding anticipation. It can be argued that the line between reaction and anticipation is blurred. "Reaction" seems to imply a response to an already unfolding event, whereas "anticipation" suggests the prediction of an event that may only occur with some probability. However issues arise when defining what perceptual features constitutes the event itself, and it may be impossible to determine when an event is absolutely certain to occur, meaning that every reaction could contain some element of anticipation. Conversely, anticipating athletes may simply have learned to "react" to cues that appear ambiguous to the untrained observer, but almost always precede a certain outcome. Biomechanical studies suggest that visual information becomes more reliable the closer it is to the execution of the action to be anticipated (Navia et al., 2018). As mentioned before, elite soccer players also tend to rely more on postural cues right before action execution (Gredin et al., 2018) and this very late perceptual information has proven especially useful when the opponent makes a deceptive move (Wright et al., 2013). If expert soccer players wait to anticipate until right before the opponent's action execution, are they truly anticipating or simply reacting when the opponent can no longer inhibit a certain response? To support this latter notion, research indicates that better goalkeepers rely on reaction rather than anticipation when defending against a shot at the goal (Navia et al., 2018). Thus, there seems to be a tradeoff between speed (anticipation) and accuracy (reaction). Anticipation may allow a player to respond to an opponent's action quicker, but the response may prove ineffectual if perceptual information is unreliable. Reacting may allow a player to respond to an opponent's action more accurately, but the response may come too late to be effective. Ultimately, anticipation may be detrimental or beneficial depending on the situation. While for some actions it may be better to wait and react, others may occur so quickly that a player must rely on anticipation instead.

Overall, there is strong evidence that skilled soccer players are better at anticipating the behavior of other players than less skilled players. When anticipating, skilled players seem to utilize both postural cues, contextual information, and strategic knowledge of patterns. However, due to a lack of intervention studies and studies that compare individuals of a similar skill level, it remains uncertain to which extent anticipatory ability enhances soccer performance. Just as elite players utilize different kinds of information in an adaptive manner when anticipating, anticipation itself might be most useful when it is relied upon flexibly depending on the circumstances. When the actions of opponents and teammates occur too quickly to allow for a reaction, anticipation can be a useful way to create an understanding of the current play situation and thus allow for earlier initiation of the next phase of the perception-action cycle: action selection.

3.1.4 Working memory

Given its central role in retaining and manipulating consciously available information, working memory influences several stages of the perception-action cycle. Chiefly, working memory serves as the store for the information that makes up the situational assessment of Stage 1. Through working memory the assessment is carried over to Stage 2, where it activates representations in procedural long-term memory (see Section 3.2.1). Within Stage 2 working memory is thought to play a different role, as it contributes to conscious executive processes that bias the action selection process. In this section we focus on the functions of working memory related to Stage 1, whereas Stage 2 functions are described in Section 3.2.2.

The relationship between working memory and soccer has been investigated extensively. Several studies have compared performance on working memory tasks to measures of soccer performance. Working memory capacity is typically measured with classical cognitive tests such as varieties of the operation span task, which require participants to retain and manipulate multiple pieces of information, or via multiple object tracking tasks. Studies have shown a link between multiple object tracking ability and more successful passes (Romeas et al., 2016). Further, soccer players tend to exhibit better executive functioning, including working memory, than athletes from non-strategic sports (Yongtawee et al., 2022) as well as a higher workload capacity during fast decision-making (Wang et al., 2020). Vestberg et al. (2012) have shown that Swedish national team soccer players outperformed lower ranking professional players on the design fluency test, a test of working memory and executive functioning, and in another study, researchers found that a design fluency score could substantially account for a player's coach-rated soccer ability (Vestberg et al., 2020). On the other hand, one study found no relationship between working memory and creative decision-making on a computerized soccer-related decision-making task (Furley and Memmert, 2015), and another study failed to find differences in working memory abilities between soccer players of different skill levels (Glavas et al., 2023). Both studies used tasks specifically designed to measure working memory rather than a broader array of executive functions, and as such, their negative results may cast doubt on a selective positive influence of working memory on soccer performance. Taken together, results from this first line of studies are inconsistent and significant effects may depend on how broad a test of working memory is used as well as the choice of outcome measure.

Another category of research investigates the relationship between working memory and soccer performance by overloading working memory with irrelevant information or distractor tasks to measure the impact on simultaneous performance of a soccer related task. This line of studies is in part inspired by research from basketball, which has found that lower working memory capacity is related to how much a player will be distracted by irrelevant information during a match (Ashford et al., 2021). In soccer it has been shown that auditory distractions impact performance negatively for both elite players and novices on a tactical decision-making task (Glavas et al., 2023), and that the beneficial effects of prior contextual information on decision-making is lessened when a distractor-task must be performed simultaneously (Gredin et al., 2020). Together, this line of findings indicates that the degree of load on working memory is important for soccer performance.

Some research supports a "circumvention of limits"-hypothesis, which suggests that experts in a field can bypass the normal capacity limitations of working memory by relying on other memory systems to perform tasks quicker and more efficiently (Glavas et al., 2023). Specifically, some argue, extensive experience in soccer facilitates a separate domain-specific long-term-working-memory system (LT-WM) that can quickly retrieve and apply game-relevant information and patterns from long-term memory with no additional load to (short-term) working memory (Ericsson and Kintsch, 1995). This process may be closely related to pattern recognition skills (see

Section 3.1.2). Support for LT-WM in soccer comes from studies showing that skilled soccer players generate more relevant choice options in computerized soccer decision tasks than less skilled players (Belling et al., 2015), can recognize and classify game situations quicker and more accurately than their less skilled counterparts (Lex et al., 2015), and can recall information from past matches with greater accuracy (Ashford et al., 2021). Further, a series of studies conducted by Roca et al. (2021, 2013, 2011) show a tendency for more skilled players to apply more advanced memory representations to soccer-related problem solving. Together, these findings support the assumption that elite soccer players have developed a domain-specific executive system, which can quickly retrieve and apply game-relevant information from long-term memory, as proposed by LT-WM theory. In further support of this, studies investigating the effect of non-conscious priming have revealed that quickly showing a soccer-related picture, which is later shown again to prompt a decision, can lower the response time for that decision for soccer players but not for non-players (Zoudji and Thon, 2003). Further, in an experiment with a shorter interval between prime and decision, a priming effect was shown for both novices and experts, but as working memory was overloaded with a secondary task, the priming-effect remained only for experts (Zoudji et al., 2010). These findings indicate that elite soccer players can efficiently utilize a separate memory system when information has not been registered consciously or when working memory is overloaded. However, while Glavas et al. (2023) did find that working memory capacity predicted speed and accuracy on a computerized soccer decision-making task, there was no interaction between working memory capacity and level of expertise. This indicates that experts and novices relied on working memory to a similar degree when solving problems. This finding goes against LT-WM-theory, which would predict that experts rely less on working memory because of their separate soccer-specific memory system. A systematic review on the factors distinguishing expert and novice performance in the integration of perceptual information by Brams et al. (2019) also finds more support for other theories than LT-WM. Rather than more efficient encoding and retrieval of visual information, they primarily found that expert performance was characterized by superior attentional allocation and perceptual ability.

Overall, the evidence supports the importance of working memory functions in soccer: When working memory is overloaded, performance tends to suffer. Also, more skilled players tend to perform better on working memory tasks, though results may vary depending on how broad a measure of working memory is used. Some studies used very broad measures of working memory function such as the design fluency test (Vestberg et al., 2020; Vestberg et al., 2012), which is also a measure of several executive functions. This makes it difficult to determine to which extent findings should be ascribed to working memory or other related concepts such as cognitive flexibility and control (see also Section 3.2.2). Further, some evidence suggests that highly experienced soccer players redelegate information normally processed by working memory to a separate domain-specific memory system, but the evidence for this is mixed, and it seems that elite players still rely on working memory to a significant extent. Finally, it is difficult to empirically disentangle the involvement of working memory in guiding perception and attention (Stage 1) from its role in influencing response selection (Stage 2). Since most studies simply measure the effect of working memory on the final decision outcome, it cannot readily be determined at which points in the cognitive processing it contributes.

3.2 Stage 2: action selection and execution

3.2.1 Activation and selection between response options

Based on the assessment of the current situation from Stage 1, the player must decide which action to make. Our model conceptualizes the decision making process as a competition between response options, where the starting point is a comparison of the current play situation to representations of similar situations in long-term memory. Through extensive experience as a soccer player, certain actions have been linked to positive or negative outcomes in particular situations. For the elite player the situational assessment is highly specific, implying that very few actions (and sometimes only one) are associated to it. Neural populations in the brain's motor systems related to each of these actions are activated at the beginning of Stage 2, but as only one action can be carried out, the actions compete for selection. This competitive process essentially constitutes an implicit evaluation of response options that results in the selection and execution of an action. There are two main determinants of the evaluation: First, how closely the present situation matches similar patterns in long-term memory. This matching also includes the player's current proprioceptive state, that is, the readiness to perform certain actions. Second, how strongly the different actions have been linked to these patterns (the player's response biases). By integrating these two factors, the selection process can combine present information with previous experience to maximize the probability for a successful outcome of the chosen action. The selected action also implies an expectation of its likely outcome, based on previous learning, which feeds into Stage 3 (i.e., assessment of outcome and feedback-based learning; see Section 3.3).

We assume that for elite soccer players, the action selection process occurs largely at an unconscious level, since decisions must be made fast and intuitively to take advantage of dynamic opportunities as they occur during the game. This is a different process in amateur players, where conscious deliberation seems to be more prominent (Starkes et al., 2004). The assumption is supported by research on both soccer and other team sports, which shows that a greater level of conscious processing with more deliberation time typically reduces the quality of decisions (Ashford et al., 2021; Fawver and Janelle, 2019). Whereas conscious thought is restricted by the capacity limitations of working memory, unconscious processing can evaluate several choice options simultaneously, and in any given situation during a soccer match, multiple response options are presumably relevant. It is highly unlikely that each option is sequentially considered and weighed against the others within consciousness, as this would take far too long (Petiot et al., 2021). Some studies have used verbal reporting to reveal superior recall and more sophisticated usage of memory by expert players in the context of soccer-related decision making (Roca et al., 2021, 2011). Such findings seem to indicate the use of conscious processing during action selection. The validity of these findings can however be questioned, since video-based tests without time restraints are probably quite dissimilar to real soccer matches and their fast coupling between perception and action (Zhao et al., 2022). Also, participants could retrospectively construct probable explanations for their own decisions. Instead, decisions may be "pre-reflected" in the sense that players are conscious of the decision itself but not the exact processes that gave rise to it Petiot et al. (2021).

The action selection processes are much harder to access empirically than Stage 1 processes. In previous sections we have described how more skilled players generally make quicker, better, and more creative decisions in soccer related tasks (Belling et al., 2015; Hüttermann et al., 2019; Wirth et al., 2018). Additionally, we have shown how proficiency in Stage 1 processes can predict superior decision making (Ashford et al., 2021; Belling et al., 2015; Glavas et al., 2023; Hüttermann et al., 2019; Lex et al., 2015; Natsuhara et al., 2020; Roca et al., 2018), and how changes in stimuli will impact decision making (Causer et al., 2013). However, whereas we can observe visual exploration behavior or measure working memory capacity with standardized tests and correlate these results with a decision making outcome, a player's decision making proficiency *per se* is hard to measure: Since the response selection is based on the situational assessment it is difficult to determine if poor decision making is due to poor response evaluation, or if the evaluation was accurate but based on a poor situational assessment. Some studies have attempted to measure the evaluation process through retrospective verbal reporting of participants' thinking during decision making (Roca et al., 2021, 2011). However, if the evaluation process for elite players is largely unconscious, verbal reporting of conscious thinking is not representative for on-field decision making. Because of the difficulties in measuring unconscious action selection, the literature on decision making in soccer is lacking in this important respect, and we therefore turn to general research on motor-related decision making.

Our modeling of the response selection processes at Stage 2 relates closely to the affordance competition hypothesis by Cisek (2007). This theory suggests that motor decision making depends on a competition between populations of neurons representing different movement options in a fronto-parietal system that integrates sensory, memory, and motor related information. As the current situation is perceived, it triggers response options based on past experiences of similar scenarios. The relevant response options compete, and while neurons within populations representing the same action will excite each other, neurons from different populations tend to inhibit each other. Eventually one neural population reaches a critical activation threshold, outcompetes the others, and the associated action is executed. Structures in the basal ganglia may function as gatekeepers for response selection in this process (Kalivas and Nakamura, 1999). The competition is resolved based on an ongoing analysis of costs, risks, and rewards (Cisek and Kalaska, 2010). The affordance competition hypothesis presents several explanations for decisional behaviors observed in soccer. As mentioned above, less familiar scenarios and fewer available good solutions tend to produce slower decision making (Ashford et al., 2021). Additionally, reaction times on decision tasks generally increase with the number of relevant options available (Czyż, 2021). The first finding can be explained neurophysiologically by the relatively lower activation in neuronal populations when the match between a current situation and stored representations is poor due to limited previous exposure to such scenarios. The second finding can be explained neurophysiologically by the fiercer competition between neural populations that will inhibit each other when no obvious decision presents itself. In both cases it will take longer for a neural population to reach the activation threshold, resulting in the observed slower response. Further, these neurophysiological considerations may help explain the "take-the-first" heuristic, which is prominent within team sports like soccer and suggests that a skilled player will typically pick the first viable response option that presents itself (Petiot et al., 2021). This heuristic could simply reflect behavior in scenarios that have become so familiar to players that response evaluation entails almost no competition, and a highly practiced motor response can be initiated almost immediately.

Another central point of the affordance competition hypothesis is that decision making is a continuous process representing an ongoing interaction between environment and actor (Cisek, 2007). Much research on decision making in soccer presents participants with a limited number of decision options at the same time, usually without requiring a complex motor response and with quite a lenient timeframe for response. However, decision making on the soccer field may correspond more closely to what can be termed embodied decision settings, where the environment is constantly changing and affords new response options in a way that blurs the lines between perception, decision, and execution (Gordon et al., 2021). From an evolutionary perspective, animals generally benefit from being able to adjust chosen decisions as new information comes online. Indeed, studies suggest that individuals executing a motor response will sometimes suddenly change their minds and switch course mid-action, when new information presents itself and makes another response more beneficial (Cos et al., 2021). This highlights that both situational assessment and action selection continues well into motor execution, which includes the preliminary processes in the body and muscular system associated with this. Additionally, neuroimaging research generally supports the notion of an integrated anatomical network of perceptual, knowledge-based and motor-related areas where the same neurons are continually involved in all processes (Cisek and Kalaska, 2010). For our model, this means that action selection is continuously on-going and that each processing stage is updated as new perceptual and cognitive information becomes available. The situational assessment from Stage 1 will continue to update and bias response selection in Stage 2, and even after motor execution has begun, a new decision may reach the activation threshold and change motor behavior in another direction. Conversely, difficulties in reaching a decision at Stage 2 may initiate more explorative behavior at Stage 1 to provide sufficient information for the decision, so the two stages function in an interactive manner. Here, our model differs from classical tenets of information processing, which assumes decision making to be a sequential procedure of functionally and neuroanatomically distinct processes that are each completed before the next can begin: first perception, then decision, then execution (Cisek and Kalaska, 2010).

Though the specific details of motor control processes are very relevant for soccer in general, and as targets for systematic training, they do not fall within the explanatory scope of our cognitive model. However an important general point is that motor competence, the ability to execute a particular movement pattern, is a precondition for action selection. For example, a bicycle kick requires very specific motor skills and is not part of the action repertoire of most amateur soccer players. This implies that the neural and bodily activity corresponding to a bicycle kick is not activated during Stage 2 for such players. However, given appropriate physical fitness, this may be altered by training of this particular motor skill, in which case the option of a bicycle kick can enter Stage 2's action selection in relevant play situations. Another way of describing this is that a motor representation of a bicycle kick now exists in the player's procedural long-term memory, from which it can be activated by relevant situational cues perceived at Stage 1.

In this section we have argued for Stage 2 as a competition between response options, in which the activated options are evaluated based on a match between the situational assessment, stored situational representations, and the strength of associations between these representations and specific actions. While there is limited research on the processes involved in action selection specifically for soccer, mainly due to their unconscious and elusive nature, research from the general field of motor decision making supports the idea of a competitive decision making process. The affordance competition hypothesis offers a theoretical framework for this process, including a description of action selection as a continuous process that regulates decisions all the way until they are carried out.

3.2.2 Executive functions

Whereas the action selection process itself is essentially non-conscious, its outcome can be influenced by conscious intentions and other cognitive control processes. This adds flexibility to an otherwise automatically driven behavior, which presumably is very important in a dynamic and complex game like soccer. Conscious control also leaves room for coordination between players in the form of team strategies and instructions from the coach. On the other hand, as discussed in the previous section, there seems to be a trade-off between the flexibility offered by cognitive control and the speed gained by automatic reactions. Cognitive control can take many different forms, which fall under the general heading of executive functions. Executive functions are typically divided into core and higher-level processes. Core executive functions are relatively basic control processes that belong to one of three main categories: mental shifting, information updating, and inhibitory control (Diamond, 2013; Friedman and Miyake, 2017; Miyake et al., 2000). Information updating is closely related to working memory function as it was described in relation to Stage 1 (see section 3.1.4). Higher-level executive functions combine several core processes for handling of complex tasks, for example in relation to planning, reasoning, and creative problem solving. There is some general evidence that executive functions are important in sports. For example, Jacobson and Mattheus (Jacobson and Matthaeus, 2014) found that athletes tend to outperform non-athletes on tests of inhibition and problem solving, and Rahimi et al. (2022) found that athletes in strategic sports (such as soccer) scored higher on response conflict tasks than athletes in non-strategic sports (such as track-and-field). Executive control functions are also relevant to processes at Stage 1, especially orienting behavior, but as mentioned in Section 3.1.1 this is not directly addressed in the empirical literature.

In soccer research executive functions are typically investigated by standard cognitive tests such as Trail Making B (mental shifting), Stop-Signal and Stroop tasks (response inhibition), and Design Fluency (higher-level executive processes). Several studies have reported that skilled soccer players tend to score better than average on such cognitive tests, and that the executive scores correlate with actual play performance. Vestberg et al. (2012) studied two groups of players: Swedish national league players (High-division; HD) and players of lower divisions (LD). They compared scores on the Design Fluency test between these groups, as well as a standardized norm group. Both the HD and LD players scored much better than the norm group, and the HD players also scored significantly better than their LD counterparts. Furthermore, a significant positive correlation was found between the Design Fluency score and the number of goals and assists two seasons later. Vestberg et al. (2020) followed up by showing that Swedish national team players scored significantly higher on the Design Fluency test than lower-ranking professional players (as well as much better than the norm group). The effect was specifically driven by the third Design Fluency subtest, which is the most cognitively complex part of the task. In addition, this test score correlated significantly with coach-rated game intelligence as well as with the number of assists (but not goals) made during a season. These findings support the notion that high-level executive functions are related to the ability to adaptively "read the game" that is highly valued in soccer.

Another topic that is related to flexible action selection in soccer is creativity. Creativity can be defined as the ability to produce solutions that are both novel and appropriate across different situational contexts (Roca et al., 2018). In soccer, creative tactical actions are typically more surprising to opponents than conventional playing and can provide an important competitive advantage. Indeed, Kempe and Memmert (2018) found that national teams exhibiting a higher degree of creativity in their goal scorings progressed further in the FIFA World Cup tournaments in 2010 and 2014. As mentioned in Section 3.1.1, creativity in soccer seems related to a higher degree of visual exploration (Roca et al., 2018). This is in line with our model's assumption that flexible response generation at Stage 2 is related to more elaborate information gathering processes at Stage 1, which tend to activate more than a single response option. Knöllner et al. (2022) also found significant correlations between tests of executive and visual functions in elite soccer players, further pointing to connections between these two cognitive domains in soccer. Presumably, the level of creativity in soccer players is also related to training and match-playing policies in different clubs, but to our knowledge this has not yet been systematically investigated. Higher levels of creativity could result both from conscious choices of playing attitude as well as automatic, overlearned processes established by training regimes that emphasize response flexibility.

In summary, executive functions can be assumed to be highly relevant for skilled soccer performance, mainly due to the response flexibility they provide. In line with this general theoretical point, there is some empirical evidence that performance on higher-level executive tests is positively related to match performance. Creativity is an important aspect of response flexibility, and seems related to more elaborate perceptual exploration at Stage 1. However, the empirical evidence on executive functions in soccer is still quite limited. Methodological concerns have also been raised about the reliability and validity of executive tests, which were typically developed for clinical purposes, in the different context of sport research (Furley et al., 2023). For example test impurity may be problematic, as executive functions to a large degree work through other cognitive functions, which complicates the interpretation of results. A related point is that studies using soccer-specific tasks and naturalistic research designs are still lacking in this research field.

3.3 Stage 3: assessment of outcome and feedback-based learning

3.3.1 Behavioral learning and reinforcement

When the action has been fully carried out the player perceives the outcome. In our model this stage completes the perception-action cycle by modifying cognitive and neural settings for future situations. This way Stage 3 provides a crucial learning element to the whole process. The outcome is perceived as either successful or unsuccessful relative to the intention for the action, but to a varying degree. Scoring a goal at a decisive moment in the most important match of the year probably represents one of the highest levels of perceived success, whereas a simple pass in a low-stakes situation implies a more moderate outcome evaluation. In any case, the assessment of the action outcome is subjective in nature and not necessarily equivalent to the objective costs or benefits for the team. Instead it relates to the player's personal goals and level of self-interest, which may overlap with the team, but can also – for example in case of social competition between teammates - be contrary to the collective aim. The learning impact of the assessment is closely coupled with the player's expectations for the outcome, which is an inherent aspect of the action produced in Stage 2: An action with a low expectation of success, such as a long shot at the goal, will lead to stronger behavioral feedback if successful than an action which the player expects to carry out well every time. Vice versa, failure of a normally successful action leads to stronger behavioral feedback than failure of an action with a low expected probability of success.

This general principle relates to the theory of reward prediction error, which states that the difference between predicted and received rewards is the central mechanism for behavioral learning (Glimcher, 2011). At the neurophysiological level prediction errors are indexed through up- and downregulation of activity in dopaminergic neurons, which signal the amount of deviation from the predicted outcome (Schultz, 1998). Given the widespread projections of the dopaminergic system to anterior parts of the brain, this activity can influence many cognitive processes, in particular those related to action selection. In our model this corresponds to plastic changes in the relative balance between excitation and inhibition of specific responses at Stage 2. The dopaminergic activity also feeds back to the orientation movements at Stage 1 that immediately preceded the action, and reinforces this behavior either positively or negatively. This way the assessment of the action outcome makes the player either more or less likely to repeat the associated behavior in similar future situations.

Soccer-related studies of these learning processes are still in their infancy, but Häusler et al. (2015) published an fMRI study that showed overlap in mesolimbic dopaminergic activity between monetary and social (soccer-related) rewards. This indicates that the general neural mechanisms of reward learning also apply in the context of soccer. In addition, Häusler et al. (2015) found an interaction with egoism personality scores, so that activation of the left middle frontal gyrus when scoring indirectly via a pass versus by a direct shot correlated with this personality measure. These are interesting pioneer findings, but clearly much more research is needed to bridge the empirical gap between general theories of behavioral learning and soccer-specific processes. At present, our case for the relevance of the reward prediction error theory in soccer rests on its status as a highly established general theory, not on direct evidence in the field of soccer research.

3.3.2 Attentional reorienting, perceptual learning, and metacognition

The outcome assessment has other effects on the player's cognitive processes than modification of automatic action tendencies. These other effects relate both to the attentional and perceptual processes at Stage 1 as well as the executive control over response processes at Stage 2. As described in the previous section the dopaminergic feedback mechanisms also influence orientation behavior at Stage 1. Given the close coupling between exploratory behavior and attentional focus (Rizzolatti and Luppino, 2001) these behavioral modifications imply changes in attentional processes, for example a stronger tendency to monitor a particular spatial direction if something unexpected just occurred from there. However the outcome assessment also has effects on purely perceptual processes, especially relating to pattern recognition and anticipation. The ability to recognize and predict dynamic play configurations in soccer can be assumed to depend on the accumulated experience from many thousands of individual situations (Ericsson et al., 1993; Williams et al., 2012). Every time a player perceives the outcome of a play situation, a small modification is made to these highly specialized perceptual abilities. The long-term result of this learning process is the general advantage that elite players hold over less skilled players in terms of pattern recognition and anticipation in soccer, as described in Sections 3.1.2 and 3.1.3.

The executive control processes at Stage 2 are also influenced by the outcome assessment. In particular, the risk taking aspect of response selection can be assumed to depend on the current confidence level of the player. Feelings of confidence are closely related to metacognitive processes, where metacognition can be defined as the ability to monitor the accuracy of one's own cognitive and behavioral functions (Fleming, 2024; Fleming and Frith, 2014). The confidence level for a given ability is dynamically modified by individual experiences when performing a given activity (Rouault et al., 2019). This way, the outcome assessment can provide the necessary feedback to continuously modify (positively or negatively) the player's feeling of confidence, and thereby the tendencies to select particular actions.

4 General discussion

In this paper we have presented a three-stage model of the cognitive processes involved in each play situation of soccer at the elite level. The model provides an integrating theoretical frame for how cognitive processes interact during high-level soccer play. It includes the main cognitive processes that have been studied empirically in soccer research, but also points to a number of important processes that are as yet little investigated. In the following we discuss the empirical and theoretical basis of the model, its applied perspectives, and implications for future research.

As detailed in the review section of this paper, the model relates directly to specific fields of investigation in cognitive soccer research. The model can accommodate the wide variety of findings in this empirical literature, and it provides a general organizing frame for cognitive soccer research. However our review also points to several important limitations in the current evidence. First, a large part of the existing research is laboratory-based, but cognition and behavior in these settings does not necessarily translate to real-life play. Indeed, several studies point to important differences between performance in laboratory and real-life settings, for example in relation to gaze patterns. For this reason there is a growing acknowledgement that studies should use research designs and tasks that are more representative of real play situations, and compare cognitive measures directly to match performance. While the methodology for such naturalistic soccer studies has been developing rapidly in the last few years, there is still limited evidence to bridge the gap between measures of cognition in laboratory environments and actual match performance. Second, the large majority of situations for players during a soccer match do not involve ball possession, but rather positioning for defensive or attacking purposes. However, studies of cognitive processes associated with positioning behavior are virtually absent in the empirical literature. Third, even under controlled experimental conditions, it remains difficult to empirically disentangle the different cognitive processes that contribute to soccer behavior. This is especially the case for processes that are involved at multiple processing stages, such as working memory and executive functions, and for the unconsciously operating mechanisms of action selection. Fourth, there is sparse evidence on many details of the processes included in our model, for example soccer-specific pattern recognition, involvement of other sensory systems than vision, individual differences in risk taking during response selection, or the different learning mechanisms of Stage 3. This way, even though much progress has been made in cognitive soccer research over the last two decades, the ecological validity of many studies can be questioned, and important questions remain unanswered. This implies that many aspects of our model await further validation.

Partly due to these limitations of the soccer literature, our model relies significantly on general theory and evidence from the wider research fields of cognitive psychology and neuroscience. For Stage 2 we apply general principles from the affordance competition hypothesis to describe action selection in soccer. This well-established theory of motor-related decision making should be highly relevant to soccer: both the speed and sensory-motor nature of soccer makes an embodied decision making approach more appropriate than traditional cognitive models of decision making, which rely heavily on (slow) conscious deliberation. The affordance competition hypothesis describes a parallel competition process between action programs, which might seem at odds with the overall serial format of our model. However, as emphasized several times in the paper, our model includes parallel and interactive processes both within and between the three main processing stages. The affordance competition hypothesis is therefore fully compatible with the other elements of the model. Still, our account of Stage 2 rests mainly on general theoretical considerations rather than direct evidence on how actions are selected by soccer players. The same is the case for the feedback processes of Stage 3, where we apply general principles of cognitive and neural learning from the reward prediction error theory and other research. Also with regard to these learning processes, soccer-specific empirical studies are much lacking. While it is reasonable to assume that decision-making and learning processes in soccer follow the same principles as human cognition and behavior more generally, the lack of direct evidence is a significant limitation of our model, which will have to be addressed by future studies.

Professional soccer is performed in a high-pressure environment, and an important question is how emotions and stress-related factors influence the cognitive processes described in the model. Emotions can have both positive and negative effects on sport performance (Vast et al., 2010) and are likely to influence many different cognitive functions (Smith and Lane, 2015). For this reason emotions or stress-related processes are not associated with specific parts of our model, but should rather be considered as general modifying factors across the whole perception-action cycle. That said, some cognitive processes are probably more vulnerable to stress and intense emotionality than others. It is often suggested that relatively attention-demanding processes, in particular executive control functions, are more susceptible to emotional influences [for a recent study of this in soccer players, see Knöbel et al. (2024)]. Conversely, automatic processes like pattern recognition and highly overlearned responses are typically more robust to emotional pressure. Attention-dependent processes are also related to arousal and cognitive effort (Kahneman, 1973), both of which can be influenced by stress and emotionality. In a soccer context these processes have mainly been studied in relation to mental fatigue [see Soylu et al. (2022) and González-Víllora et al. (2022) for recent reviews of this emerging research field]. Also, following the classical work of Kahneman (1973), changes in pupillary size may function as a marker for cognitive effort in soccer (Cardoso et al., 2019). Clearly, much interesting research awaits to be done on the interaction between emotional arousal and cognition in soccer.

Due to its cognitive specificity and coverage of the whole perception-action cycle our model has important applied perspectives, especially in relation to professional soccer training. For example the model allows for a detailed analysis of the cognitive processes involved at Stage 1, which can potentially widen the focus of training to include pre-decision processes rather than the currently dominating focus on decision making and situational outcomes. As we argued in Section 3.2.1, a decision to perform a certain action can only be as good as the preceding situational assessment allows, so it is very important to optimize Stage 1 processes. From an analytic perspective the advantage of such an approach is also that, whereas the outcome of a given tactical situation depends on many external factors, a player's cognitive preparation before making an action can be analyzed more specifically. Visual orientation behavior is for example readily observable by video analysis. We would argue that such observational studies could be performed by the analysis department possessed by most elite soccer clubs, and that these data could be supplemented by standardized testing of specific cognitive abilities for each player. Such combined analyses could give a more complete and individualized understanding of the decision making processes of elite soccer players, and provide a basis for training specific cognitive aspects thereof. This cognitively focused training could be organized in a periodization structure or via individual development plans for each player. The details of such periodization structures and training methodologies are however beyond the scope of the present article.

Based on our theoretical model and review of the empirical literature we would like to conclude this paper with some general suggestions for future research. To address one of the most important limitations of the existing research on cognition in soccer, it is important to expand the recent trend toward more naturalistic studies. Specifically, in the pursuit of experimental tasks and measures that are more representative of actual soccer play, studies that focus on positioning behavior rather than ball possession would be very informative. The influence of emotional factors on cognition in soccer is another underdeveloped research area with huge potential relevance for professional performance. Finally, important scientific advancements could be gained from research designs that include cognitive interventions. Contrary to the correlational designs that have been used in most soccer studies so far, experimental interventions that systematically manipulate cognitive variables can address mechanisms of causality more directly. Such research designs are also better suited to disentangle the contribution of different cognitive processes to behavioral outcomes, which is currently a major limitation for interpreting the evidence. If the cognitive interventions represent activities that can transfer to professional soccer training, such studies would also have large applied perspectives.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

Ethics statement

Ethical approval was not required for the studies involving humans because the manuscript does not include own empirical data, but analyzes and discusses previously published studies of soccer players. The studies were conducted in accordance with the local legislation and institutional requirements. Written informed consent for participation was not required from the participants or the participants' legal guardians/next of kin in accordance with the national legislation and institutional requirements because we did not collect data from participants.

Author contributions

TH: Conceptualization, Investigation, Methodology, Supervision, Writing – original draft, Writing – review & editing. JO: Conceptualization, Investigation, Methodology, Writing – original draft, Writing – review & editing. JM: Conceptualization, Supervision, Visualization, Writing – original draft, Writing – review & editing.

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Conflict of interest

JM was employed by F. C. Copenhagen during earlier phases of the research and by the Saudi Pro League during completion of the article.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Differences in spatiotemporal pressure and performance between Chinese and German elite youth football players during matches

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Introduction: In modern football, spatial and temporal pressure significantly influence player performance and tactical outcomes, particularly in youth competitions. This study aims to investigate the spatial pressure differences between Chinese and German U17 elite youth football teams, focusing on the ball-handler's distance to the nearest defender (D).

Methods: Video analysis was conducted to measure D across various match contexts, including scorelines (leading, tied, and trailing), game phases (passing and receiving), pass outcomes (successful and unsuccessful), and pitch zones. Statistical analyses were performed using non-parametric methods to compare the D under different conditions. The Mann–Whitney *U* test and Kruskal–Wallis *H* test were used to identify significant differences, with *post hoc* comparisons conducted where necessary.

Results: Results show that the German team consistently maintained greater D than the Chinese team ($p < 0.001$, $d = 0.463$), highlighting their superior spatial management and tactical adaptability.

Discussion: Greater D was associated with enhanced offensive flexibility and defensive stability, allowing the German team to create space effectively and maintain structural integrity under pressure. In contrast, the Chinese team's smaller D suggested limitations in spatial utilization and higher defensive engagement risks. These findings underscore the importance of tactical training emphasizing spatial awareness and balanced pressure management, providing valuable insights for youth football development.

KEYWORDS

spatiotemporal analysis, youth football, pressure, performance, tactics

1 Introduction

In modern football, the time interval between transitions from attack to defense is becoming shorter, and the frequency of these transitions is increasing. High-intensity defensive tactics are considered a key component of future games (Nassis et al., 2020; Harper et al., 2021). Effective defending can significantly increase the pressure on the attacking side, leading to a higher "level of pressure" on players and preventing the opposition from organizing successful attacks, thereby reducing the likelihood of conceding goals for the defending team (Link et al., 2016). Defensive pressure primarily refers to the spatial pressure exerted by defenders on attacking players, aimed at limiting the actions available to attackers. It is often correlated with the performance of the defending team (Andrienko et al., 2017; Tenga et al., 2010).

Currently, high-pressing defensive tactics are gaining popularity, and research related to defending is continually evolving. Tengahe and Fernandez-Navarro, among others, have highlighted the differences in pressure exerted by various playing styles but have not provided conclusive results on the effectiveness of different defensive pressing behaviors (Fernandez-Navarro et al., 2020; Lepschy et al., 2021). At the same time, research on the attacking side is equally important, as it enables players to better manage their psychological state under pressure, thus maintaining their performance without being disturbed by mistakes (Chen et al., 2023). However, it remains difficult to determine the actual effect of pressure in football matches, with much of the existing literature offering subjective conclusions. Furthermore, research on pressure in youth football is scarce, with most studies focusing on adult athletes (Garcia et al., 2015; Coutinho et al., 2017). Understanding how defensive pressure manifests in youth football is crucial, as it not only influences tactical outcomes but also shapes the technical and psychological development of young players. Within a cross-cultural context, differing training methodologies may result in varied interpretations and applications of defensive strategies. Consequently, by examining defensive pressure in youth football, this study seeks to highlight its broader implications for player development and team performance. This study addresses these issues by focusing on how defensive pressure manifests in youth football across Germany and China, two countries with contrasting football cultures and training methodologies.

It is noteworthy that European football coaches place particular emphasis on training at the youth level (Forcher et al., 2024). Training scenarios are often set in small-sided games (SSGs) that simulate match-like conditions, aiming to enhance essential competitive skills in football (Herold et al., 2022). Therefore, training content in each session should cover approximately 70–80% of game-related scenarios. In contrast, the proportion of training dedicated to attacking and defensive situations in Chinese youth football is sometimes as low as 20%, a disparity that significantly impacts players' understanding of the game (Gao et al., 2023).

Despite the growing focus on defensive pressure in football, there is limited understanding of how these metrics apply specifically to youth players, whose developmental and tactical approaches differ from adult athletes. Furthermore, cross-cultural analyses of defensive pressure remain underexplored, leaving gaps in how training philosophies and tactical systems shape defensive strategies in different footballing contexts. This study addresses these issues by focusing on how defensive pressure manifests in youth football across Germany and China, two countries with contrasting football cultures and training methodologies.

This study aims to analyze the characteristics of defensive pressure faced by youth players in different attacking scenarios during matches. Specifically, it seeks to compare the performance of Chinese and German youth football players, identify the characteristics of successful defending, and explore cross-cultural differences in defensive strategies. By addressing these objectives, the study aims to enhance the understanding of spatiotemporal dynamics in youth football and provide actionable insights for improving training practices.

To achieve this, the study focuses on two teams from contrasting football contexts: Germany, one of the world's leading football nations with a high football participation rate, and China, a country that has made considerable efforts to develop football despite its relatively low football population density. This study hypothesizes that German youth players, with their emphasis on positional play and spatial management, will exhibit greater defensive distances compared to their Chinese counterparts. Conversely, Chinese players are expected to display higher intensity in defensive actions, reflecting their tactical focus on pressing and rapid transitions.

This study fills a critical gap in the literature by focusing on youth football, an area less explored compared to adult football. Adopting a cross-cultural perspective, it examines tactical differences and their roots in distinct training philosophies. The findings aim to quantify spatiotemporal defensive characteristics, highlight cross-cultural differences between Germany and China, and provide practical insights to enhance youth football training across diverse contexts.

2 Materials and methods

2.1 Materials

This study compared the Under-17 (U17) teams of the German Bundesliga club TSG 1899 Hoffenheim and the Chinese Super League club Beijing Guoan, both competing at the highest level of their respective national youth leagues. To maintain consistency and alignment with the research objectives, U17 matches were selected for analysis after initial video monitoring across multiple age groups (U15, U17, and U19). Two matches per team were chosen from four recorded games to ensure competitive balance and comparability. The German matches were sourced from the 2017 and 2018 German Youth Bundesliga (1st Division), while the Chinese matches were taken from the Chinese Football Association Super League (1st Division). All selected matches were home games to ensure consistency in the video recording setup. Matches were carefully selected to ensure competitive quality, with closely contested outcomes, high technical and tactical performance, and balanced competition. Efforts were made to minimize external factors, such as adverse weather conditions, that could affect match quality or recording clarity. To reduce seasonal variability, all matches were recorded within a two-month summer period.

While this study analyzed two matches per team to maintain balance, it is acknowledged that the limited sample size may restrict the generalizability of the findings. These matches were selected based on their competitive level and representativeness, ensuring that the data provided meaningful insights despite the constraints. Additionally, it is recognized that tactical variability, such as formations and individual roles, may influence the observed metrics. However, this study focuses on overarching defensive pressure characteristics rather than specific tactical nuances. These limitations highlight the exploratory nature of this research and lay the groundwork for future studies to expand the dataset and incorporate tactical factors for a more comprehensive understanding.

2.2 Protocol

Before the recording process, the pitch in each stadium was carefully calibrated to ensure precise spatial measurement. Pylons were strategically placed at specific points along the field's boundary to aid in the calibration process. This setup ensured that the camera remained stationary throughout the game, eliminating any need for panning or zooming and thereby maintaining consistent image quality and perspective across all recordings. GoPro cameras (HERO14 Black) were employed for video recording, positioned 5 m away from both the centreline and the sideline at a fixed height, as shown in Figure 1. This configuration allowed for a comprehensive and unobstructed view of the pitch. The calibration process played a crucial role in linking the pixel-based coordinate system of the video to a predefined coordinate system on the field, enabling accurate spatial measurements of players' movements and interactions.

2.3 Data processing

The data processing phase involved multiple steps to ensure the accuracy and reliability of the collected data. Video preprocessing was conducted to eliminate distortions. Utilized field calibration was performed on each frame to link pixel dimensions to real-world coordinates. A predefined field coordinate system was applied, enabling precise calculation of the relative positions of players and the distances between them (Laakso et al., 2017; Vilar et al., 2014; Winter, 2009; Duarte et al., 2010; Duarte et al., 2012). This step ensured accurate spatial measurements across all video data.

To analyze the data, a custom MATLAB (MathWorks, United States) program was developed. This program automatically identified the ball-possessing player and the nearest defensive player in each frame and measured the distance between these two players. This distance was used as a proxy for pressure, based on the principle that a shorter distance indicates higher defensive pressure exerted on the ball-possessing player. In comparison, a greater distance suggests reduced pressure and more freedom for decision-making and action. This metric allowed for a quantifiable assessment of spatiotemporal pressure during different phases of the game. Data extraction and annotation were conducted to classify actions into three categories: releasing the ball, receiving the ball, and starting a dribble. Key metrics such as success, player ID, and location were annotated. Additional subdivisions for middle and side lanes were used to provide a detailed examination of distances and interactions across these zones, helping to identify patterns of offensive and defensive pressure.

Following data extraction and annotation, the overall distance metric was represented as total D (D_{Total}). Specific distances were recorded for key game scenarios, including the distance at the moment of ball release ($D_{Release}$), the distance when receiving the ball ($D_{Receive}$), the distance during successful passes ($D_{Success}$), and the distance during failed passes (D_{Fail}). Additionally, distances were measured based on the ball-handler's position on the field: in the 30-meter goal zone (DGoal_zone_30m) and in the middle field zone ($D_{Midfield\_zone}$). To account for match context, distances were also recorded according to the real-time scoreline: when the team was leading (D_{Lead}), tied (D_{Tie}), or trailing (D_{Behind}). This classification enabled a detailed analysis of spatiotemporal dynamics across various phases and conditions of play. To ensure data reliability, all extracted distances were manually cross-verified, and any discrepancies were resolved through a frame-by-frame review process. This comprehensive approach ensured the accuracy and robustness of the data used for subsequent analyses.

2.4 Statistical analysis

The data were compiled and subjected to statistical analysis using Excel 2021 and SPSS 27.0 (IBM, United States). The normality of the data was assessed using the Kolmogorov–Smirnov test. The homogeneity of variance was evaluated using Levene's test. All data are presented as median (interquartile range, IQR). Non-parametric tests were employed to compare differences in D between Germany and China under different conditions, as well as D within the same team across different conditions. For comparisons between two

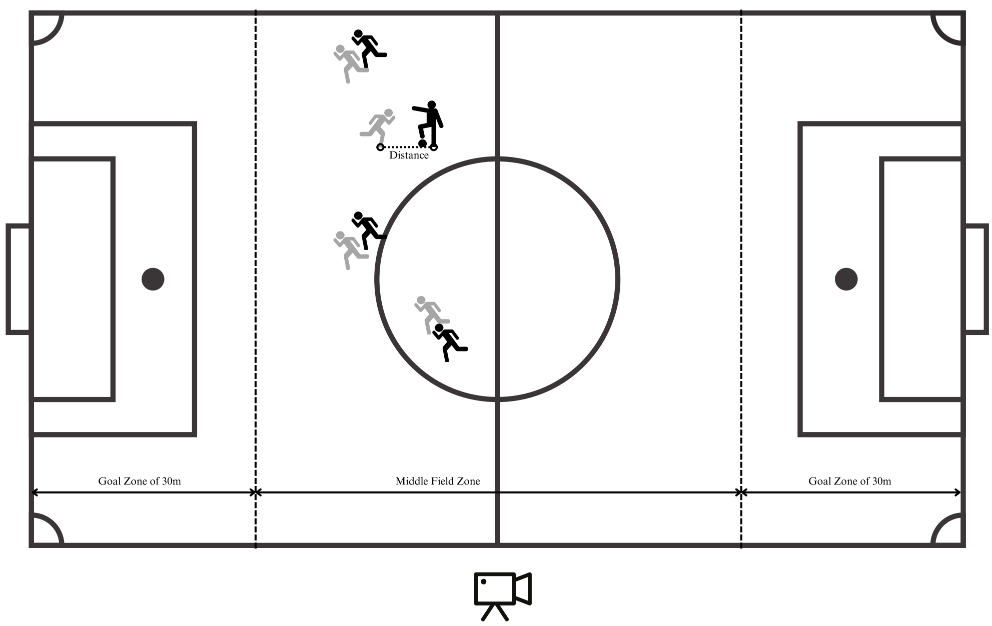

FIGURE 1
Schematic diagram of the experimental protocol.

groups, the Mann–Whitney U test was used, and for comparisons involving more than two groups, the Kruskal–Wallis H test was applied. *Post hoc* pairwise comparisons were conducted using Dunn's test for multiple comparisons when significant differences were detected. Effect sizes for pairwise comparisons were reported using Cohen's d. Cohen's d greater than 0.8 was considered large, between 0.8 and 0.5 as medium, between 0.5 and 0.2 as small, and less than 0.2 was considered insignificant. For comparisons involving more than two groups, Cohen's f was used as the effect size measure, with Cohen's f greater than 0.40 considered large, between 0.40 and 0.25 as medium, between 0.25 and 0.10 as small, and less than 0.10 as insignificant. The significance level was set at $p < 0.05$.

3 Results

3.1 Differences in ball-handler distance to nearest defender between Chinese and German teams

The comparison of the overall match data reveals that the D_{Total} of the German team was significantly higher than that of the Chinese team ($p < 0.001$, small). Under conditions where the actual score was in favor of the team, the D_{Lead} of the German team was significantly higher than that of the Chinese team ($p < 0.001$, small). During instances when the score was level, the D_{Tie} of the German team was significantly higher than that of the Chinese team ($p < 0.001$, medium). Under conditions where the score was unfavorable, the D_{Behind} of the German team was significantly higher than that of the Chinese team ($p < 0.001$, medium). At the moment of ball release, the $D_{Release}$ of the German team was significantly higher than that of the Chinese team ($p < 0.001$, small). At the moment of ball reception, the $D_{Receive}$ of the German team was significantly higher than that of the Chinese team ($p < 0.001$, medium). Under conditions of successful passes, the $D_{Success}$ of the German team was significantly higher than that of the Chinese team ($p < 0.001$, small). Under conditions of unsuccessful passes, the D_{Fail} of the German team was significantly higher than that of the Chinese team ($p = 0.001$, small). With the ball-handler positioned in the 30-meter goal zone, the $D_{Goal\_zone\_30m}$ of the German team was significantly higher than that of the Chinese team ($p < 0.001$, medium). With the ball handler positioned in the middle field zone, the $D_{Midfield\_zone}$ of the German team was significantly higher than that of the Chinese team ($p < 0.001$, small). As shown in Table 1, the results described above are presented. While the findings are statistically significant, the small to medium effect sizes suggest varying degrees of practical impact. Medium effect sizes observed in D_{Tie}, D_{Behind}, and $D_{Receive}$ highlight the German team's advantage in maintaining greater spacing, which may allow for better defensive organization in dynamic or high-pressure scenarios. Conversely, the small effect sizes in metrics such as D_{Lead} and $D_{Success}$ indicate that greater spacing is less influential when the team is already leading or executing successful passes. These results reflect contrasting defensive strategies and highlight the German team's adaptability to different game conditions.

3.2 Variations in ball-handler distance to nearest defender under different conditions between Chinese and German teams

The ball-handler distance to the nearest defender for the German team exhibited significant differences across conditions where the team was leading, level and trailing in the score ($p = 0.001$). The ball-handler distance to the nearest defender for the Chinese team also demonstrated significant differences across the conditions of leading, level and trailing in the score ($p < 0.001$). The D_{Tie} of the German team was significantly greater than the D_{Lead} ($p = 0.009$). However, no significant difference was observed between the D_{Tie} and the D_{Behind} ($p = 0.460$). The D_{Behind} of the German team was significantly greater than the D_{Lead} ($p < 0.001$). For the Chinese team, the D_{Lead} was significantly greater than the D_{Tie} ($p < 0.001$), and the D_{Behind} was also significantly greater than the D_{Tie} ($p = 0.001$). However, there was no significant difference between D_{Lead} and D_{Behind}. As shown in Table 2, the results described above are presented. The results of the multiple comparisons are presented in Figure 2. These findings reveal tactical contrasts in defensive spacing under different score conditions. The German team maintained wider spacing during level and trailing scenarios, suggesting a focus on flexibility and counterattacking. In

TABLE 1 Comparison of ball-handler distance to nearest defender between German and Chinese teams in various match situations.

Variable	GER	CHN	z	p	d
D_{Total}	5.176(2.947,9.283)	3.578(2.078,5.982)	−11.944	<0.001**	0.463
D_{Lead}	4.741(2.596,8.614)	3.858(2.131,6.533)	−4.279	<0.001**	0.250
D_{Tie}	5.318(2.892,10.258)	2.954(1.582,4.899)	−8.101	<0.001**	0.696
D_{Behind}	5.646(3.174,9.386)	3.719(2.289,5.933)	−9.162	<0.001**	0.595
$D_{Release}$	4.245(2.499,8.042)	3.114(1.785,5.094)	−7.789	<0.001**	0.440
$D_{Receive}$	6.334(3.600,10.711)	4.029(2.428,6.903)	−9.942	<0.001**	0.525
$D_{Success}$	5.504(3.057,9.663)	3.731(2.164,6.235)	−11.351	<0.001**	0.462
D_{Fail}	3.694(2.263,6.228)	2.828(1.685,4.506)	−3.308	0.001**	0.471
$D_{Goal\_zone\_30m}$	4.105(2.420,7.807)	2.980(1.736,4.693)	−5.313	<0.001**	0.509
$D_{Midfield\_zone}$	5.615(3.073,9.828)	3.746(2.189,6.260)	−11.192	<0.001**	0.475

The data are presented as median (interquartile range); z: Mann–Whitney test statistic z-value; d: Cohen's d; Cohen's d greater than 0.8 was considered large, between 0.8 and 0.5 was categorized as medium, between 0.5 and 0.2 was considered small, and less than 0.2 was deemed insignificant; $^*p < 0.05$, $^{**}p < 0.01$ for differences between teams.

TABLE 2 Variations in ball-handler distance to nearest defender under different score conditions for German and Chinese teams.

Teams	D_{Lead}	D_{Tie}	D_{Behind}	H	p	η_p^2	f
GER	4.741(2.597,8.614)	5.318(2.892,10.258)	5.646(3.174,9.386)	14.254	0.001**	0.008	0.087
CHN	3.858(2.131,6.533)	2.954(1.583,4.899)	3.719(2.189,5.933)	16.368	<0.001**	0.012	0.109

The data are presented as median (interquartile range); H: Kruskal–Wallis test statistic H-value; f: Cohen's f; Cohen's f greater than 0.40 was considered large, between 0.40 and 0.25 was categorized as medium, between 0.25 and 0.10 was considered small, and less than 0.10 was deemed insignificant; $*p < 0.05$, $**p < 0.01$ for differences between conditions.

contrast, the Chinese team tightened spacing during level scores to limit opposition opportunities, with less variation between leading and trailing situations. These patterns highlight the teams' differing strategies and adaptability to match dynamics.

For both the German and Chinese teams, the $D_{Release}$ was significantly greater than the $D_{Receive}$ ($p < 0.001$, Cohen's $d = 0.412$, small; $p < 0.001$, Cohen's $d = 0.319$, small). For the German team, the $D_{Success}$ was significantly greater than the D_{Fail} ($p < 0.001$, Cohen's $d = 0.431$, small); similarly, for the Chinese team, the $D_{Success}$ was also significantly greater than the D_{Fail} ($p < 0.001$, Cohen's $d = 0.403$, small). For the German team, the $D_{Midfield\_zone}$ was significantly greater than the $D_{Goal\_zone\_30m}$ ($p < 0.001$, Cohen's $d = 0.281$, small); likewise, for the Chinese team, a similar pattern was observed, with the $D_{Midfield\_zone}$ being significantly greater than the $D_{Goal\_zone\_30m}$ ($p < 0.001$, Cohen's $d = 0.332$, small). The variations and differences mentioned above are illustrated in Figure 3. The small effect sizes observed across these scenarios suggest that while the differences in defensive spacing are statistically significant, their practical impact may be subtle. These findings imply that the observed variations likely reflect incremental adjustments rather than fundamental shifts in tactical strategies. Such adjustments, though modest, can influence the efficiency of defensive responses, the ability to control space, and the success of transitions, particularly in high-stakes moments.

4 Discussion

The findings of this study demonstrate clear differences in D between Chinese and German youth football teams across various conditions. German players consistently maintained greater D compared to their Chinese counterparts, irrespective of match context or phase of play. This suggests that German players may prioritize the creation and utilization of space as a tactical advantage, reflecting superior spatial awareness and positioning strategies. Notably, under conditions where the team was leading, level, or trailing, the German team's D was significantly greater than that of the Chinese team. Moreover, in critical phases such as ball release and reception, as well as during successful versus unsuccessful passes, the German team's D surpassed that of the Chinese team, underscoring their capacity to generate space during both offensive actions and transitions. This spatial advantage was evident across different field zones, with midfield zones displaying greater distances compared to goal zones for both teams, albeit more prominently for the German team. These results highlight potential disparities in tactical training and match execution between the two teams.

Such findings align closely with established theories in football science, which emphasize the pivotal role of space creation and positional discipline in tactical execution. Previous studies provide valuable insights into how distance metrics contribute to both offensive and defensive strategies. Emphasizes for instance, studies have shown that players' positional coordinates are fundamental for understanding tactical behavior, particularly in relation to the distance between attackers and defenders, as well as the space players occupy during matches (Laakso et al., 2017; Travassos et al., 2014; Silva et al., 2016). German players' ability to maintain greater D compared to their Chinese counterparts across various conditions reflects a similar tactical approach observed in other elite teams, where spatial awareness and positional discipline are crucial in maintaining effective offensive and defensive structures (Headrick et al., 2012). In line with Laakso et al. (2017), who observed larger distances between attackers and defenders in central areas of the pitch, the German team in this study showed a consistent ability to create more space, particularly in midfield zones. This finding is consistent with the broader understanding that greater spatial dispersion allows teams to maintain offensive pressure and manage defensive transitions more effectively (Laakso et al., 2017; Headrick et al., 2012). The fact that German players were more effective in maintaining greater D during both offensive and transition phases corroborates previous research that highlights the role of distance in enhancing team dynamics during ball possession and recovery phases (Menuchi et al., 2018; Shafizadeh et al., 2016). Moreover, the consistent greater D in different match contexts—whether leading, level or trailing—further supports findings from other studies that demonstrate defensive caution and spatial reorganization as key tactics in maintaining a tactical advantage during various match phases (Duarte et al., 2012). The comparison of the two teams in this study provides further evidence that distance management is not merely a function of individual skill but also a team-wide tactical strategy that reflects deeper structural and strategic principles of the game, as also suggested by Duarte et al. (2012). Thus, the observed disparities in D between Chinese and German teams suggest differences in tactical training, particularly in how teams manage space during match play. These results further support the notion that effective space management and team cohesion can influence both individual performance and team success in football (Olthof et al., 2018; Santos et al., 2017).

These tactical differences are reflected in the distinct ways both teams manage spatial dynamics during match play. Greater D provides offensive players with more time and space to make decisions, enabling cleaner passing and more effective spatial utilization (Jankowski, 2015). This approach aligns with the German team's consistent use of space in both midfield progression and goal zone positioning, where larger spacing facilitated controlled transitions and reduced the risk of turnovers. Defensively, a larger D reflects disciplined positioning that prioritizes structural integrity. By avoiding over-commitment, the German team effectively minimized the risks associated with close defensive engagements, such as being bypassed by quick passing or positional play. This strategic approach likely contributed to their consistent performance under varying match conditions, allowing them to adapt to different pressures while maintaining the balance between defense and attack (Rico-González et al., 2021). In contrast, the Chinese team's smaller D suggests a focus on close defensive engagement, such as high pressing. While this approach can disrupt an opponent's rhythm, it often leaves gaps in the defensive structure, particularly when the

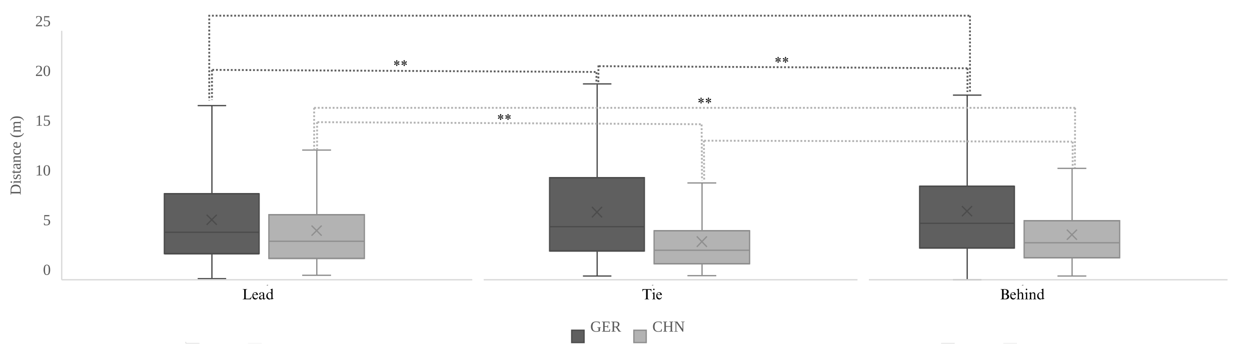

FIGURE 2
Multiple comparisons of ball-handler distance to nearest defender under three score conditions for German and Chinese teams. *$p < 0.05$, **$p < 0.01$ for differences between conditions.

initial pressure is bypassed (Low et al., 2021). Offensively, the smaller D observed for the Chinese team limited their ability to create space, leading to increased defensive interference and reduced passing options (Travassos et al., 2023). These challenges underline the limitations of a smaller D in managing both defensive risks and offensive fluidity.

The observed tactical differences between the two teams are not only a reflection of match-specific strategies but also indicative of broader systemic approaches to youth development. The German team's ability to maintain greater D and balance between offensive and defensive phases is rooted in the structural and developmental philosophies underpinning their youth football system. The German youth football system is centered on decentralized training and professional collaboration, emphasizing close coordination between youth academies, elite football schools, and the educational system (Naglo, 2020). This model has successfully produced a significant number of professional players; for instance, 80.6% of Bundesliga players born in 1993 graduated from professional youth academies (Grossmann and Lames, 2015). This structure not only ensures the professionalism of football training but also provides educational support, enabling players to balance their academic and athletic commitments. A key feature of the German training methodology is its focus on physical fitness enhancement, combined with match-scenario testing to evaluate players' tactical performance, creativity, and game intelligence (Memmert, 2010). Compared to other European nations, Germany places greater emphasis on physical conditioning within its training programs, prioritizing the holistic development of athletic performance (Roca and Ford, 2020). This balanced training approach lays a solid foundation for players' long-term success while fostering high levels of discipline and organization in tactical execution. The overall advantages of this model are evident in its combination of decentralized strategies, comprehensive fitness and tactical training, and the integration of informal activities, providing a sustainable framework for developing professional football talent. This system offers valuable lessons for other nations, particularly in balancing short-term performance goals with long-term development objectives.

In comparison to the German youth football system, China's youth football development system, while making some progress in recent years, remains underdeveloped and faces numerous pressing challenges. The system comprises professional clubs, provincial and municipal sports bureaus, urban youth training centers, school football programs, and social training organizations. However, these components lack effective coordination, with each focusing predominantly on maximizing its interests. This has led to fragmented resources and insufficient integration, ultimately hindering the efficiency and quality of youth football development (Butte and Liu, 2020). Such a loosely structured ecosystem has significantly limited the potential for fostering young football talent in China.

The centralized training system in China has exacerbated these challenges, further hindering the development of a cohesive and sustainable youth football framework. Centralized training policies, such as the U23 policy, have further highlighted the systemic issues within the youth training system. Although intended to cultivate young players for the national team, these policies have had limited success and, in some cases, have even hindered player development. For instance, age-eligible players are often restricted from participating in more high-level competitions, while overage players are excluded from opportunities to progress in their careers (Butte and Liu, 2020). This short-term, results-driven approach reflects a broader issue in China's youth football development, where the focus on immediate outcomes often overshadows the need for long-term planning (Wei, 2019). As Xiancheng (2021) research emphasizes, China's youth football training system faces significant challenges, including a low penetration rate of football participation and a shortage of talented young players.

In contrast, the German youth football system achieves systemic coordination through a decentralized management model and close integration with the education system. This ensures a structured approach to professional training while providing players with an environment where they can balance academic and football development (Wei, 2019). Compared to the youth training systems in Japan, Spain, and France, China's centralized training lacks a stable talent pipeline (Butte and Liu, 2020). Furthermore, the characteristics of early specialization and high training intensity in China's youth training system increase the risk of premature career termination among elite youth football players (Li et al., 2023).

The findings suggest that greater D offers a more balanced and effective strategy, combining offensive flexibility with defensive stability. This approach not only facilitates better decision-making for ball handlers but also reduces vulnerability to opponent counterplays. For teams seeking to enhance their tactical performance, prioritizing spatial management through maintaining a large D could be a key developmental focus.

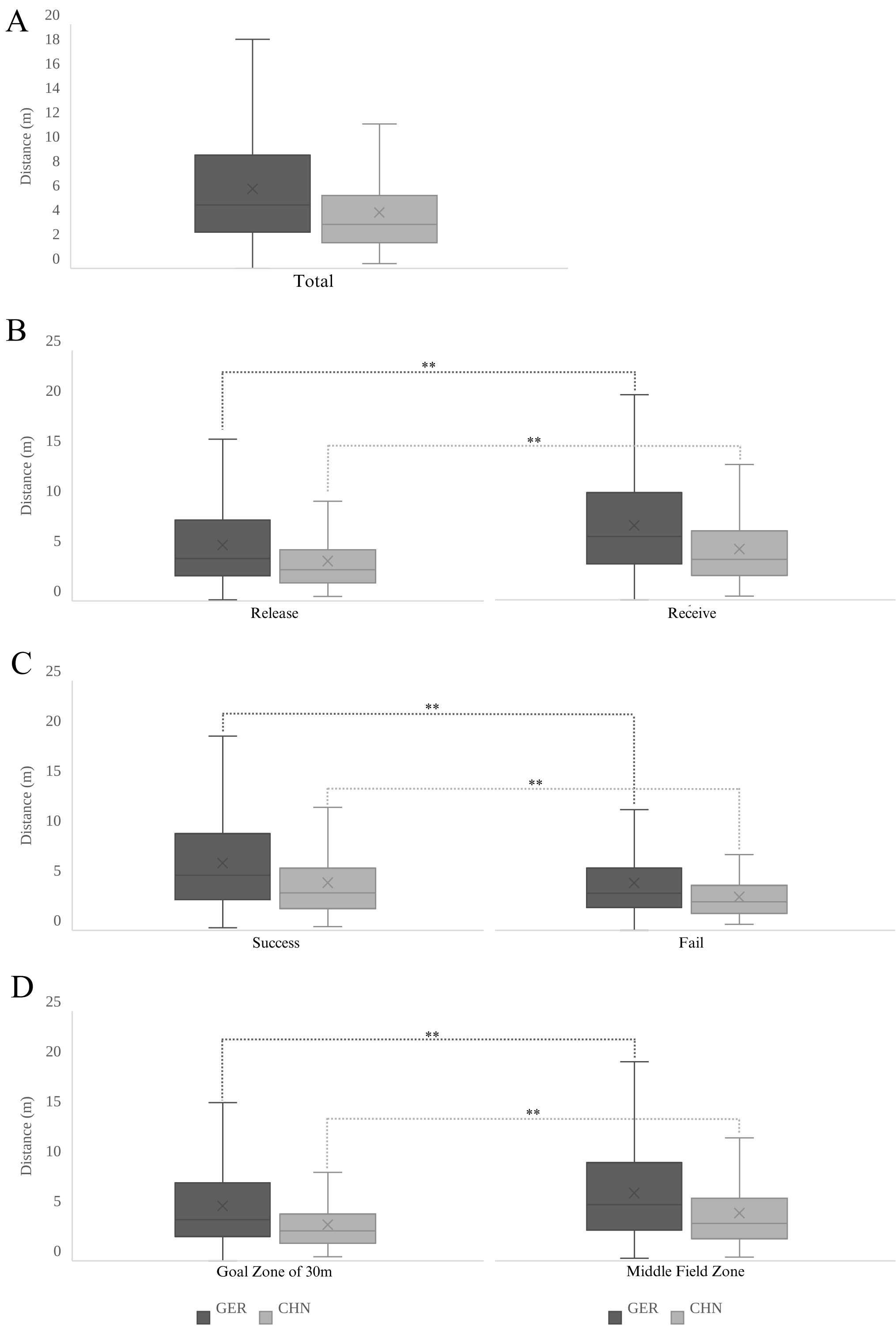

FIGURE 3
Variations in ball-handler distance to nearest defender under different conditions for German and Chinese teams. **(A)** Overall variations in ball-handler distance to nearest defender (m). **(B)** Distance variations during ball release and reception (m). **(C)** Distance variations in successful and fail passes (m). **(D)** Distance variations across different field zones (m). **p* < 0.05, ***p* < 0.01 for differences between conditions.

Video analysis tools, as employed in this study, can serve as a critical resource for monitoring and improving player performance. Coaches could use such tools to track player positioning and distances in real-match scenarios, offering objective feedback on tactical execution. For example, analyzing the distance between the ball-handler and the nearest defender (D) during key moments like ball release and reception can help identify patterns in spatial management. These insights can inform the design of targeted drills and training strategies aimed at improving spatial awareness, decision-making, and defensive coordination. Incorporating such data-driven methods into regular training sessions can bridge the gap between research findings and practical application, fostering long-term player development.

5 Limitations

The sample used in this study may not fully represent the broader characteristics of elite youth football teams in Germany and China. Factors such as team selection, competition levels, and match contexts could influence the generalisability of the findings. Expanding the sample to include diverse teams and conditions would strengthen future analyses. While D serves as a valuable proxy for assessing spatial pressure, it may not capture the full complexity of player decision-making and technical execution. Incorporating additional dimensions, such as decision quality, movement patterns, or tactical effectiveness, could provide a more holistic understanding of pressure and performance dynamics. Future research should explore the dynamic interplay between spatial pressure and performance over time, focusing on how players and teams adapt to evolving match conditions. Additionally, cross-cultural analyses of tactical development could uncover valuable insights into the relationship between training systems and spatial management strategies.

6 Conclusion

This study demonstrated significant differences between German and Chinese youth football teams across temporal, contextual, outcome-based, and spatial dimensions of play. The German team consistently exhibited greater D, reflecting superior spatial management and adaptability under varying match conditions. In contrast, the Chinese team's smaller D suggests potential limitations in tactical flexibility and space utilization. These findings offer valuable insights for tactical training and youth development. For the Chinese team, enhancing spatial awareness and adaptability in training could improve performance under diverse pressures. Additionally, reducing tendencies for overly aggressive pressing, which risks defensive disorganization, may lead to more effective pressure management. Encouraging ball handlers to increase spacing in offensive phases could also support better team coordination and reduce defensive interference. However, it is important to acknowledge that the conclusions drawn from this study are based on a relatively small sample size, which may limit the generalizability of the findings. The selected matches, while representative of typical performance, may not fully capture the variability in tactical behaviors across broader competitive contexts. Future research with larger datasets and diverse match scenarios is recommended to validate these results and further explore the implications of spatiotemporal metrics in youth football training and performance.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

Ethics statement

The requirement of ethical approval was waived by Sports Science Experiment Ethics Committee of Beijing Sport University for the studies involving humans because this study did not require ethical approval as it involved secondary analysis of publicly available match footage and did not collect any personally identifiable data from participants. The data used were observational in nature and recorded in a naturalistic setting during official matches, adhering to the guidelines of the respective football governing bodies. No interventions, experiments, or direct interactions with human participants were conducted. The studies were conducted in accordance with the local legislation and institutional requirements. The ethics committee/institutional review board also waived the requirement of written informed consent for participation from the participants or the participants' legal guardians/next of kin because written informed consent was waived for this study as the data were derived from publicly available match footage recorded in naturalistic settings during official competitions. The study involved no direct interaction with participants and no collection of personally identifiable information.

Author contributions

YL: Writing – original draft, Writing – review & editing. TL: Writing – original draft, Writing – review & editing. HX: Software, Writing – review & editing. PZ: Conceptualization, Funding acquisition, Investigation, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Goal and shot prediction in ball possessions in FIFA Women's World Cup 2023: a machine learning approach

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Introduction: Research in women's football and the use of new game analysis tools have developed significantly in recent years. The objectives of this study were to create two predictive classification models to forecast the occurrence of a shot or a goal in the FIFA Women's World Cup 2023 and to identify the associated technical-tactical indicators to these outcomes.

Methods: A total of 2,346 ball possessions were analyzed using an observational design, mapping two different target variables (Success = Goal and Success2 = Goal or Shot) with a relative frequency of 1.28 and 8.35%, respectively. The predictive capacity was tested using Random Forest and XGBoost and finally and SHAP values were calculated and visualized to understand the influence of the predictors.

Results: Random Forest technique showed greater efficacy, with recall and sensitivity above 93% in the resampled dataset. However, recall on the original test sample was 13% (Success = Shot or Goal) and 0% (Success = Goal), demonstrating the models' inability to predict rare events in football, such as goals. The indicators with the greatest influence on the outcome of these possessions were related to the possession zone, attack duration, number of passes, and starting zone, among others.

Conclusion: The results highlight the need to incorporate a greater number of predictive variables in the models and underline the difficulty of predicting events such as goals and shots in women's football.

KEYWORDS

female football, women's soccer, predictive models, machine learning, performance analysis, FIFA Women's World Cup 2023

1 Introduction

The analysis of technical-tactical performance in men's football began to develop significantly in the late 20th and early 21st centuries (Hughes and Bartlett, 2002), using notational and observational records (Preciado et al., 2019). Later, with the use of new technologies, this analysis started to be conducted on data obtained from positional sensors such as Global Positioning System (GPS) and Local Positioning System (LPM) (Low et al., 2020). In the case of women's football, the lower participation of women in the sport and a lack of social and research interest delayed the publication of the first studies by more than a decade (Kirkendall, 2007; Mara et al., 2012; Leite, 2013). A significant increase in research occurred starting in 2020, coinciding with the FIFA

Women's World Cup 2019 (Lee and Mills, 2021; Iván-Baragaño et al., 2022; Kubayi, 2022) and, later, with the FIFA Women's World Cup 2023 (Branquinho et al., 2024; Bradley, 2025a, 2025b; Iván-Baragaño et al., 2025; Oliva-Lozano et al., 2025).

Currently, Artificial Intelligence, and Machine Learning in particular, have become topics of interest for researchers and practitioners (Nassis et al., 2023; Rico-González et al., 2023), who have conducted studies with various objectives, such as establishing differences between men's and women's football (Pappalardo et al., 2021), predicting injury risk (Robles-Palazón et al., 2021), or the probability of success of different types of actions, such as entries into the penalty area (Iván-Baragaño et al., 2021; Stival et al., 2023) or shots during set-piece situations (Maneiro et al., 2019). In all of these studies, different regression and/or classification models were trained with the aim of predicting outcomes or future behaviors.

More recently, other studies have attempted to apply more complex strategies, materialized in the use of various techniques based on deep neural networks. Among the different examples of the use and application of Artificial Intelligence in the analysis of high-performance football, the article by AlMulla et al. (2023) trained a deep neural network model (Gated Recurrent Unit) to predict the outcomes of football matches in the Qatari league over 10 consecutive seasons, using data from data providers. Similarly, Wang et al. (2024) trained and evaluated a generative AI model based on deep learning and graph methods, which allowed the generation of execution proposals for set-piece actions. This was part of an unusual collaboration between Google DeepMind and Liverpool FC. Despite this, and in agreement with Claudino et al. (2019) the synergy that Artificial Intelligence needs to create alongside football still requires further development in the coming years.

This gap is even more pronounced in the case of women's football, with scarce scientific evidence where AI or ML has been applied to female samples. In this regard, some authors have sought to understand the differences between men's and women's football (Pappalardo et al., 2021) using supervised ML techniques and applying explainability methods such as SHAP values (Lundberg and Lee, 2017). On the other hand, other studies have conducted analyses of offensive play using supervised techniques such as binary logistic regression (Iván-Baragaño et al., 2022), multinomial logistic regression (Casal et al., 2023), or decision trees (Maneiro et al., 2019). Additionally, some authors (Shen et al., 2024) have proposed models focused on convolutional neural networks and computer vision to determine offensive positioning in women's football, using images extracted from UEFA Women's Champions League matches.

In any case, and as a common aspect of studies conducted using supervised machine learning classification techniques, most studies have been carried out using methods characterized by high intrinsic explainability (such as decision trees or logistic regression), but often with moderate performance. In this context, there is a need to improve the performance of predictive models applied to a chaotic and non-linear reality like football, without sacrificing interpretability, to ensure the application of these studies' results to training and competition.

For the reasons mentioned above, the objective of this study was twofold. First, it aimed to create two binary classification models that would allow the prediction of the outcome of ball possessions in elite women's football (i.e., whether the possessions end in a Goal or a Shot). Additionally, once these models were trained, the SHAP library was implemented to identify the technical-tactical performance indicators that had the greatest influence on the model.

2 Materials and methods

2.1 Design and participants

The study was framed within the systematic observational methodology proposed by Anguera (1979) employing a nomothetic design, as multiple units of analysis were examined, represented by each participating team; it featured punctual inter-sessional tracking due to the temporal association between the actions analyzed within a single match; and it was multidimensional, as the observation instrument addressed the dimensions of identification, initiation, development, and outcome of ball possessions (Anguera et al., 2011).

All ball possessions during the final phase (from the Round of 16 onwards) of the FIFA Women's World Cup 2023 were analyzed, provided they met the following inclusion criteria: (i) a minimum duration of 4 s, and (ii) the possession must involve two consecutive touches of the ball, a pass, or a shot (Almeida et al., 2014).

2.2 Observation and recording instrument

The observation instrument was created by a panel of experts, including three researchers with over 30 years of experience in observational methodology and can be consulted in Table 1. It comprised 18 criteria, and 51 categories. The analyzed criteria were organized in 4 dimensions corresponding to identification, start, development and outcome of the ball possession. The recording instrument used for this study was LINCE PLUS (Soto-Fernández et al., 2021).

2.3 Procedure and reliability

Prior to conducting the recording, the observers were trained and familiarized with the observation instrument over 4 sessions, following the procedure proposed by Losada and Manolov (2015). The reliability of the observation instrument was verified through the calculation of Cohen's (1960) Kappa coefficient for both intra- and inter-observer reliability among the study's authors. The average obtained was 0.869 (range: 0.729–0.979), which is considered excellent (Landis and Koch, 1977), based on the average of all criteria and observations made on 258 records corresponding to two matches.

2.4 Data cleaning and preprocessing

Once the data matrix was obtained, consisting of 2,346 ball possession records, the following cleaning and preprocessing tasks were performed using the Scikit-Learn library (Pedregosa et al., 2011): (i) Checking for null values (none were found), (ii) Mapping the Possession Outcome variable into two binary recodings (Recoding 1: Success = Goal or Shot, No Success = Rest of the possessions & Recoding 2: Success = Goal, No Success = Rest of the possessions), (iii) Scaling of quantitative variables using the MinMaxScaler technique due to the skewness of the distribution (Figure 1), (iv) Applying OneHotEncoding to categorical variables.

When the dataset was preprocessed, an oversampling process was performed on the unbalanced class in both recodings (Success) using

TABLE 1 Observational instrument: criteria, categories, and operational definition.

Criteria	Categories	Operational definition
Observe team	Teams analyzed	The team that executed the ball possession
Match outcome	Win	The team observed won the match
	Lose	The team observed lost the match
	Draw	The team observed draw the match
Time	1Q	Possession starts between the start of the game and minute 1
	2Q	Possession starts between minute 16 and minute 30
	3Q	Possession starts between minute 31 and the end of the first half
	4Q	Possession starts between the start of the second half and minute 60
	5Q	Possession starts between minute 61 and minute 75
	6Q	Possession starts between minute 76 and the end of the game
Match status	Winning	The team observed is winning when the action starts
	Drawing	The teams are level when the action starts
	Losing	The team observed is losing when the action starts
Start form	Set Play	Possession begins after a regulatory interruption of the game.
	Transition	Possession begins without a regulatory interruption.
Start zone (length)	Defensive	Possession begins in the defensive area of the pitch
	Predefensive	Possession begins in the predefensive area of the pitch
	Middle	Possession begins in the middle area of the pitch
	Preoffensive	Possession begins in the preoffensive area of the pitch
	Offensive	Possession begins in the offensive area of the pitch
Start zone (width)	Left	Possession starts from the left wing
	Central	Possession starts from the center
	Right	Possession starts from the right wing
Defensive organization	Organized	The opposing team is defensively organized
	Circumstantial	The opposing team is defensively disorganized
Defensive positioning	Low	Opponents positioning is at the back at the start of the action
	Medium	Opponents positioning is midfield at the start of the action
	Advanced	Opponents positioning is forward at the start of the action
Interaction context	MM	Midfield zone vs. midfield zone
	RA	Rear zone vs. forward zone
	RM	Rear zone vs. midfield zone
	A0	Forward zone vs. goalkeeper
	AA	Forward zone vs. forward zone
	AM	Forward zone vs. midfield
	AR	Forward zone vs. rear zone
	MA	Midfield zone vs. forward zone
	MR	Midfield zone vs. rear zone
	PA	Goalkeeper vs. forward zone
Offensive intention	Keep	The team observed tries to maintain possession of the ball
	Progress	The team observed tries to progress towards the rival goal
Defensive intention	No pressure	The opposing team shows an intention to defend their goal
	Pressure	The opposing team shows an intention to recover the ball
MD (seconds)		Time of possession in own half (in seconds)
MO (seconds)		Time of possession in opponent's half (in seconds)
Possession time		Total time of possession

(Continued)

TABLE 1 (Continued)

Criteria	Categories	Operational definition
Passes		Number of passes
Possession zone	MD	Most possession in own half
	MO	Most possession in opponent's half
Possession outcome	Goal	The possession ends with a goal
	Shot	The possession ends with a shot
	Sent to area	The possession ends with a ball into the penalty area
	No success	The possession ends with no success.

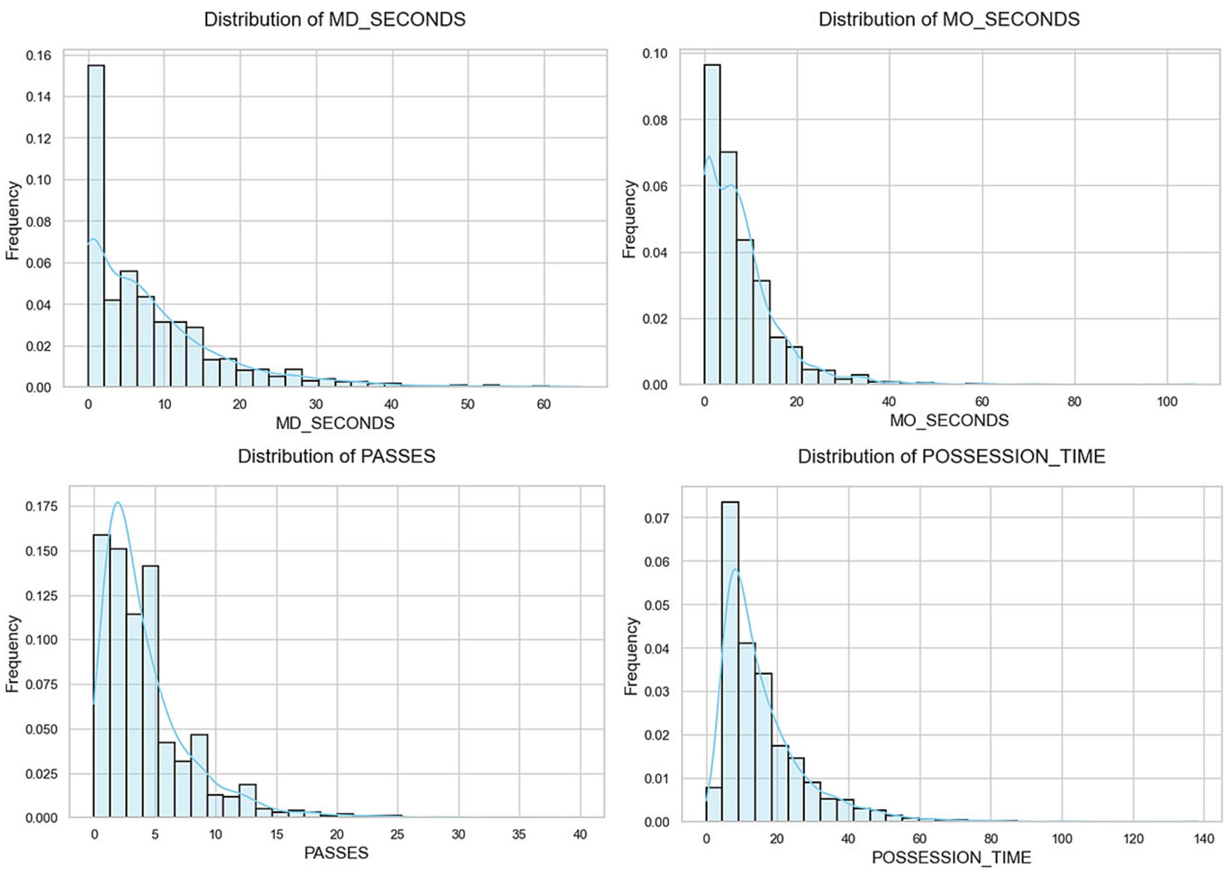

FIGURE 1
Initial distribution of quantitative variables.

the Imbalanced Learn library (Lemaitre et al., 2017) which adjusted the classes to 50%. Figure 2 presents the percentage of positive cases for the target variable, considering success as a goal (Figures 2A,B) and as both a goal and a shot (Figures 2C,D). The oversampling process was carried out using SMOTE, due to its performance in model training in other studies (Last et al., 2017).

2.5 Data analysis

Once the datasets were resampled, the supervised machine learning models were trained using the Random Forest and XGBoost techniques, both implemented in the Scikit-Learn (Pedregosa et al., 2011) and XGBoost (Chen and Guestrin, 2016) libraries, respectively. The selection of these two algorithms is justified in this work to evaluate the classification capacity of different model combinations. In this context, the Random Forest model is considered one of the most powerful Bagging techniques, while XGBoost is classified within the Boosting techniques. The search for the best model was conducted through a cross-validation procedure using 5 folds on the training sample, which consisted of 80% of the total dataset. A grid search was performed using the following combination of hyperparameters:

- Random Forest Technique: (i) n_stimators (200, 300), (ii) max_depth (None, 10, 20, 30), (iii) min_samples_split (2, 5, 10), (iv) min_samples_leaf (1, 2, 4), and (v) Bootstrap (True, False)

- XGBoost: (i) n_stimators (200, 300), (ii) max_depth (3, 6, 9), (iii) learning_rate (0.01, 0.1, 0.2), (iv) subsample (0.6, 0.8, 1), and (v) subsample_by_tree (0.6, 0.8, 1)

Once the best model was obtained, it was trained on the resampled dataset, and its performance was evaluated on both the resampled test set and the original test set. All the steps carried out are published in the following repository (https://doi.org/10.6084/m9.figshare.27109405) and the dataset is available at the following link (https://doi.org/10.6084/m9.figshare.27109414).

3 Results

For both recoding 1 and recoding 2, the Random Forest algorithm demonstrated higher performance compared to the XGBoost algorithm. The combination of hyperparameters that provided the best performance for recoding 1 (Goal or Shot) was Random Forest: (i) n_estimators = 200, (ii) max_depth = None, (iii) min_samples_split = 5, (iv) min_samples_leaf = 1, Bootstrap = False. Similarly, for recoding 2 (Goal), the best performance was achieved with the following Random Forest combination: (i) n_estimators = 300, (ii) max_depth = None, (iii) min_samples_split = 5, (iv) min_samples_leaf = 1, Bootstrap = False.

3.1 Results of the classification models

The results of the classification models are presented in the form of a confusion matrix in Figure 3. Additionally, a summary of the main evaluation metrics is provided in Table 2. Overall, the models demonstrated excellent performance on the resampled test sets (recall = 0.93 and 0.98 for the first and second recoding, respectively). However, on the original test sets, the model was unable to generalize, showing an incomplete ability to predict the "Goal" outcome, with a recall of 0.

3.2 Influence of predictor variables on the model output

Figure 4 shows the influence of predictor variables on the model output for recoding 1 (Success = Goal or Shot). It was observed that the variable with the greatest influence was the duration of the attack in the opponent's half, with higher values of this variable increasing the likelihood of a positive model output. Next, the variables with the most significant influence were the Possession Zone (dichotomous variables), confirming previous findings. Similarly, an initial offensive intention to progress increased the probability of a positive model output.

For the variable Passes, the color distribution observed on the X-axis indicated that possessions with mid-range values (purple colors located towards the right of the X-axis) increased the likelihood of obtaining a positive output. Lastly, the starting lane of possessions also had an influence: while possessions that began in the central lane increased the probability of a positive model result, those that started on the left and right lanes had a negative influence.

In Figure 5, the observed influence in 4 random cases from the original dataset is presented for each of the features recorded in those elements, which allows us to gain an individual understanding of the influence of these variables on the specific actions analyzed.

Lastly, Figure 6 presents the overall influence of the predictor variables on the model's output for recoding 2 (Success = Goal). In this model, the variable with the greatest influence was Match Outcome (Winner), followed by the variables Possession Zone (MO), Start Zone Width (Central), Possession Time in Opponent's Field, and Time (5Q). In this figure, an evident issue of collinearity between the target variable and the most influential variable in the model (Match Outcome = Winner) was observed, which may be the cause of the model's poor performance on the test set. Additionally, Figure 7 presents the local influence of the recorded features in four specific cases from the analyzed dataset, aiming to show how the probabilities of success are modified based on the recorded variables.

4 Discussion

The objective of this study was, first, to create two binary classification models that could predict the outcome of ball possessions in elite women's football. Additionally, once the models were trained, the aim was to identify the technical-tactical indicators associated with a higher probability of achieving a goal or a shot during ball possessions. To achieve these objectives, a mapping of the Possession Outcome variable was performed based on the degree of success (Goal

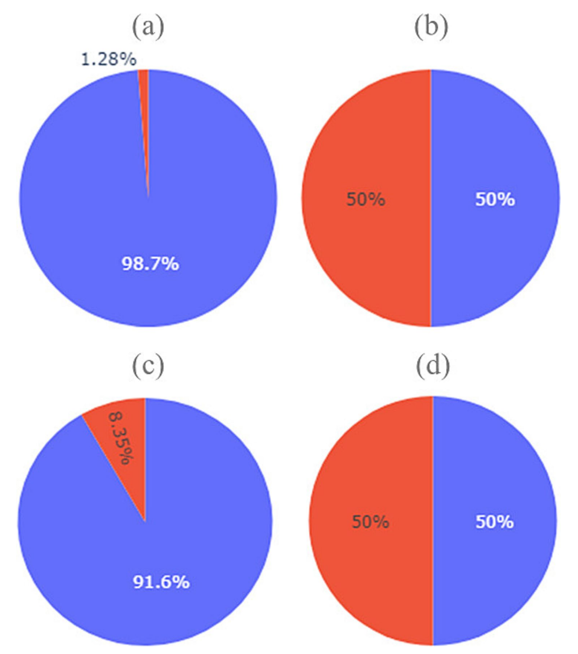

FIGURE 2
Initial distribution of success and no success classes for the two recodings before and after oversampling. **(A)** Percentage of goals in the original dataset, **(B)** percentage of goals in the resampled dataset, **(C)** percentage of goals or shots in the original dataset, **(D)** percentage of goals or shots in the resampled dataset.

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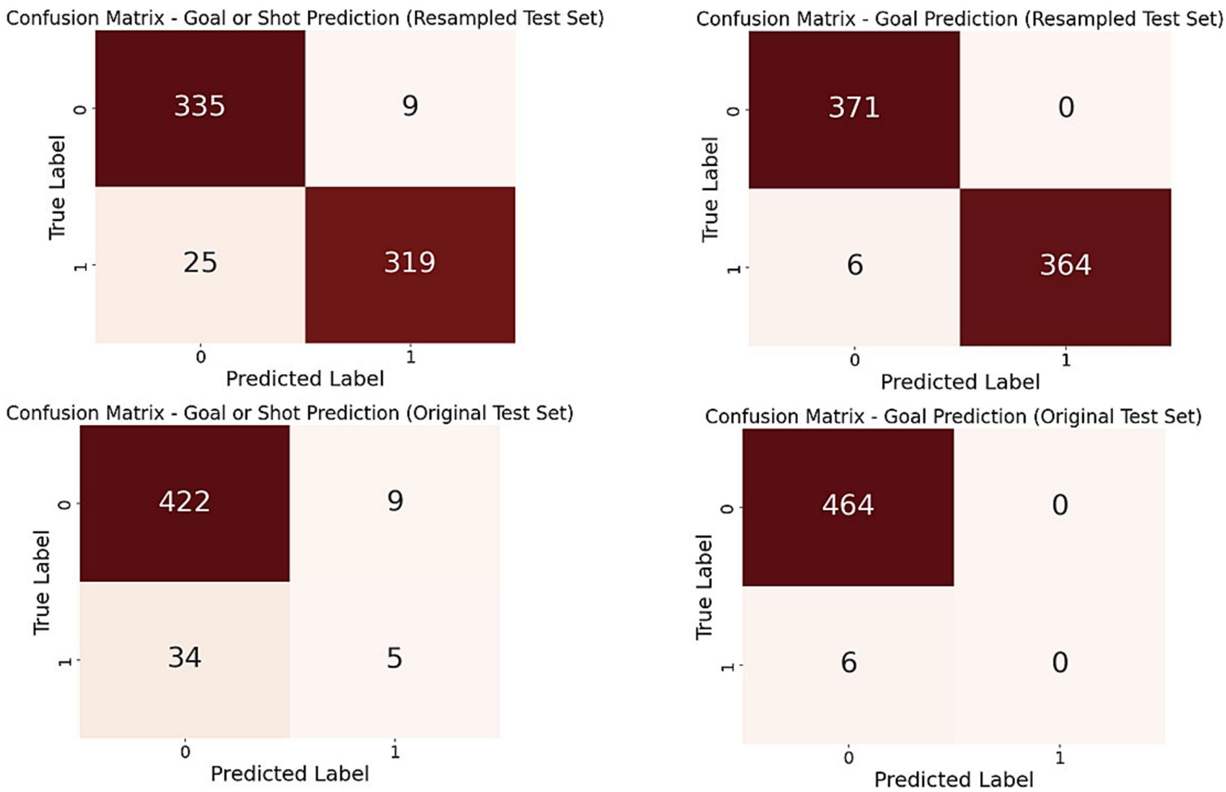

FIGURE 3
Confusion matrix of the model on the resampled and original test set (recoding 1 and 2).

TABLE 2 Summary report of the models trained.

	Goal or shot prediction		Goal prediction	
	Resampled test set	Original test set	Resampled test set	Original test set
Random Forest model				
Accuracy	0.95	0.95	0.99	0.99
Recall	0.93	0.13	0.98	0
Specifity	0.97	0.98	0.99	1
XGBoost model				
Accuracy	0.95	0.90	0.99	0.99
Recall	0.92	0.10	1	0
Specifity	0.97	0.97	0.98	1

or Shot). Following this, oversampling of the imbalanced class was conducted.

Previous studies have employed similar procedures with the aim of predicting the outcome of ball possessions in women's football. However, in most of these studies, success was defined as reaching the penalty area, reaching the final third, or, more generally, the creation of Goal Scoring Opportunities (Scanlan et al., 2020; Kubayi, 2022; Mitrotasios et al., 2022; Mesquita et al., 2023). This aspect is crucial when training a classification model, as approximately one in four (25%) ball possessions in women's football ends with a move into the final third or the opponent's penalty area (Iván-Baragaño et al., 2021; Casal et al., 2023), allowing a balance between correctly classified positive and negative cases. In contrast, in this study, the dataset showed a percentage of positive cases of 1.35 and 8.28%, respectively, which necessitated oversampling of the imbalanced classes to prevent the model from ignoring the minority class (Haller et al., 2023).

The classification models yielded excellent results on the resampled datasets, with recall and specificity exceeding 93% in both models. However, their performance on the original datasets was poor. When predicting shots or goals, the model had a recall of 13%, and in the case of goal prediction, the model did not predict any positive outcomes. These results highlight the difficulty of predicting infrequent events in football, such as shots and goals, and underscore the need for incorporating a larger number of predictor variables, as well as further tuning the hyperparameters during model training. Similarly, as seen in injury prediction, where different studies have shown recalls between 10 and 15% (Haller et al., 2023; Majumdar et al., 2024), the holistic nature of the sport contributes to the challenge of accurately predicting such events.

In relation to the SHAP technique (Lundberg and Lee, 2017) applied in this study, it was found that a large number of indicators associated with ball possessions contributed to increasing the probability of a favorable outcome for the executing team. The performance indicators associated with successful ball possessions in elite women's football observed in this work largely align with previous studies on this topic. In this regard, Maneiro et al. (2022) demonstrated that developing ball possessions in the opponent's half increased the likelihood of the possessions ending with a delivery into the penalty area. Similarly, the offensive tactical intent once ball

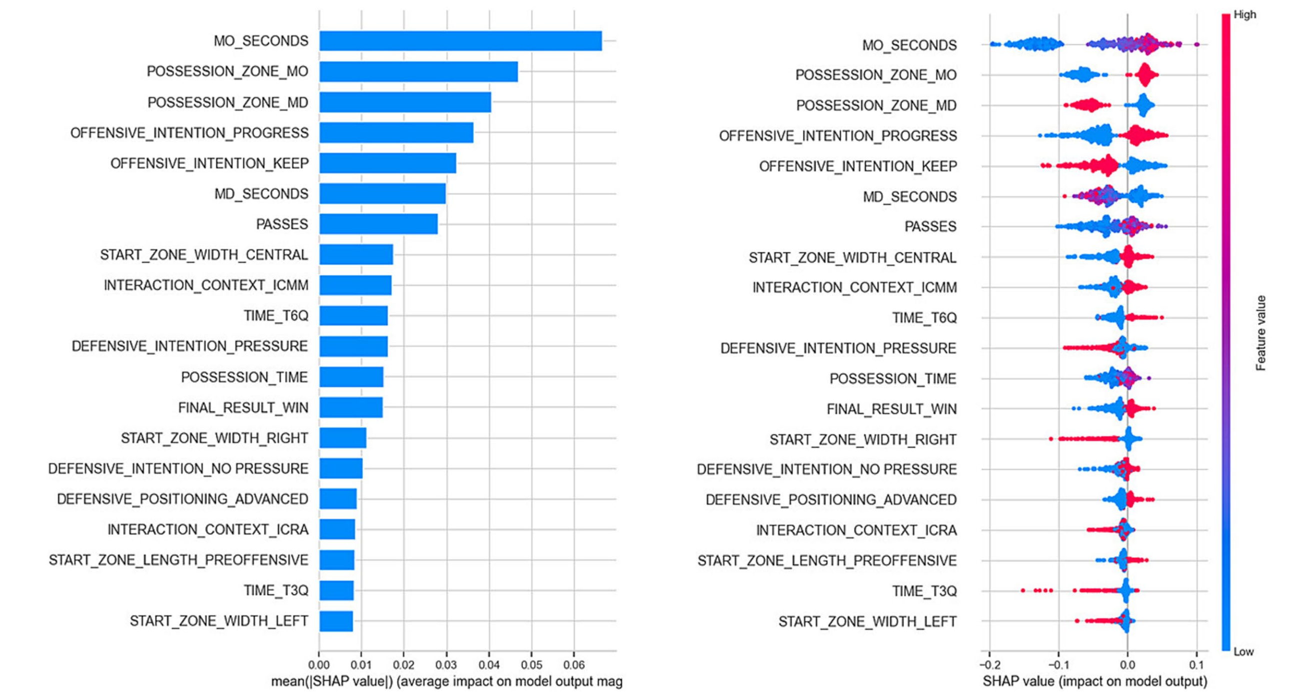

FIGURE 4
Influence of predictor variables on the model output (Success = Shot or Goal). In the left figure, the overall influence of the predictor variables is presented. In the right figure, the influence is shown based on the value of the predictor variable: pink colors indicate high values for the predictor variable, and blue colors indicate low values. For example, in the case of the first variable (MO_seconds), the blue colors are located to the left of the X-axis (below 0), indicating that when the variable has low values (short possession duration in the opponent's half), the model decreases the likelihood of predicting the positive class (e.g., Goal or Shot). Lastly, for dichotomous variables (e.g., Offensive_intention_progress), the pink colors indicate the positive class of that variable (i.e., if there was an initial offensive intention to progress, then it is more likely that the model will predict the positive class for the target variable).

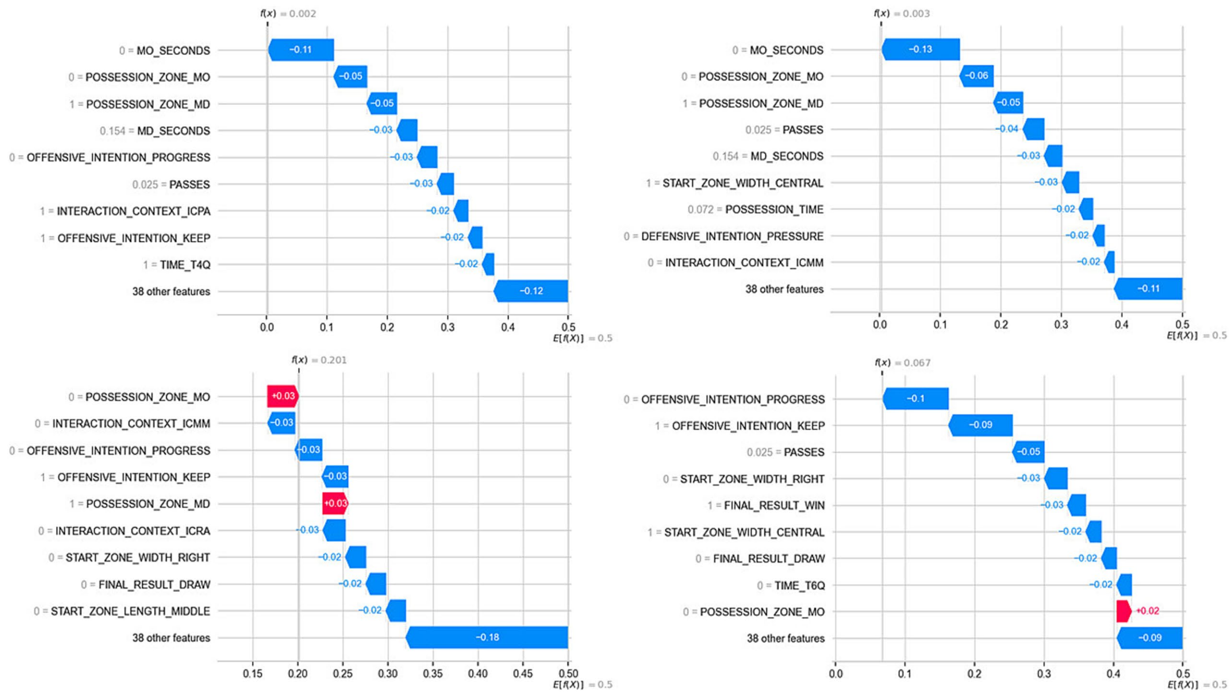

FIGURE 5
Influence of the features recorded in 4 random cases from the dataset on the model's output. Pink colors indicate an increase in the probability that the model's output will be the positive class of the target variable.

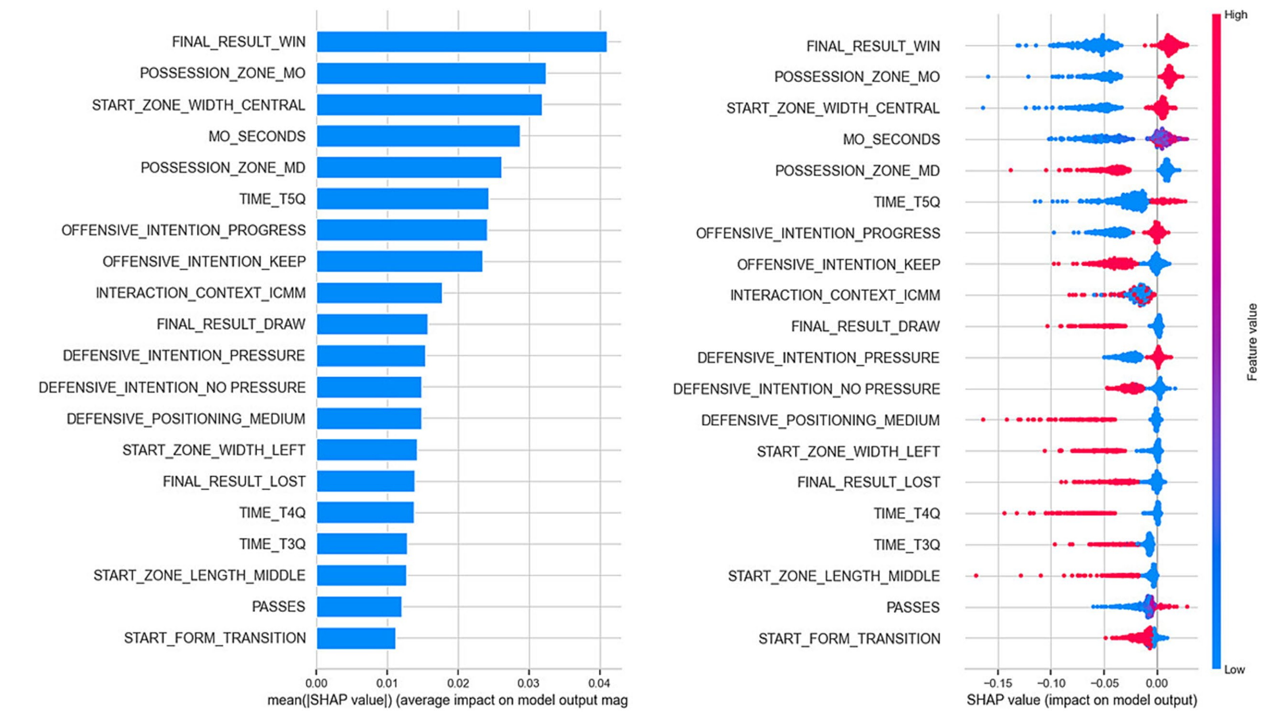

FIGURE 6
Influence of predictor variables on the model output (Success = Goal).

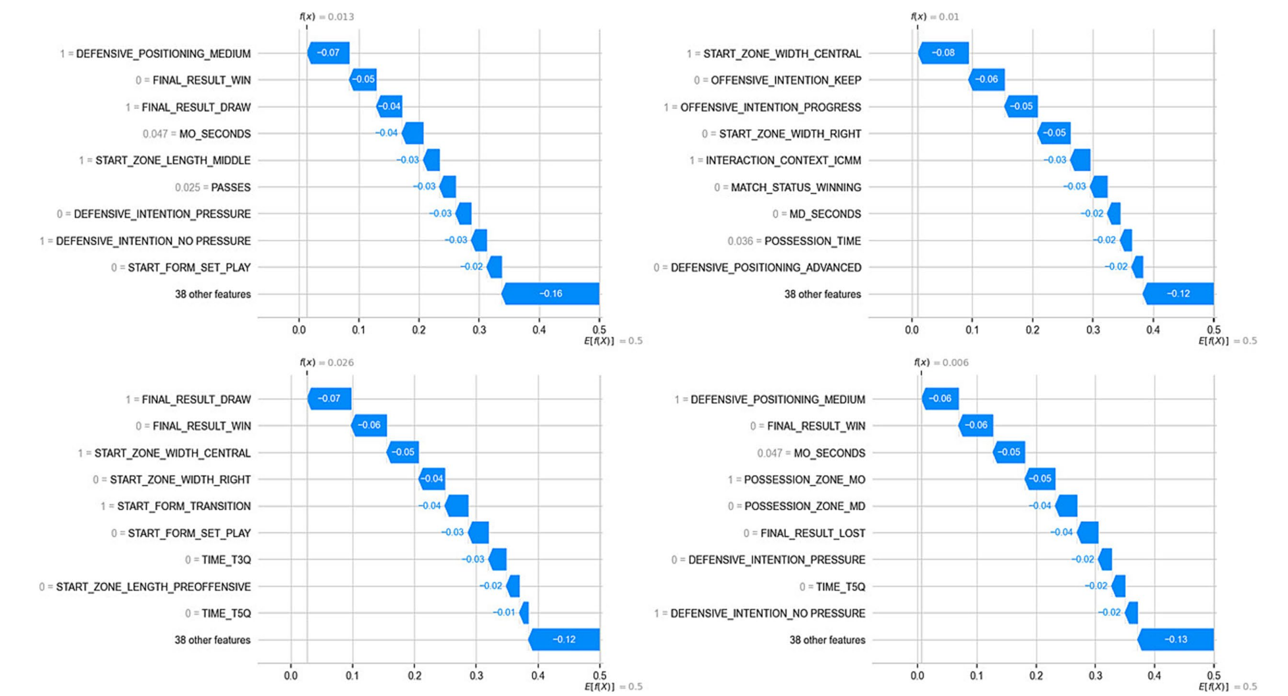

FIGURE 7
Influence of recorded features in 4 random cases from the dataset on the model's output.

possession was initiated, or the number of passes made in the offensive sequence, were variables that significantly altered the outcome of ball possessions in women's football (Scanlan et al., 2020; Iván-Baragaño et al., 2021; Casal et al., 2023).

However, considering that the level of success analyzed in this study was higher than in previous studies, this work also demonstrated the existence of variables that had not previously shown a multivariate influence on the outcome of ball possessions. For example, in the study by Iván-Baragaño et al. (2022), it was observed that the current match score had an influence on the development and outcome of ball possessions. Thus, it is interesting to note that, while success in delivering the ball into the penalty area can be influenced by the flow of the game, when it comes to taking a shot or scoring a goal, this variable does not have sufficient influence. This insight may have significant implications for the sport, as it could suggest that when teams are losing, they tend to deliver the ball into the penalty area more often but are less successful in converting these deliveries into shots or goals.

Similarly, it is interesting to analyze the influence of the variables Time (5Q and 6Q) and Start Zone Width (Central). According to the SHAP values generated for these variables, the following insights can be drawn. When predicting a shot, the likelihood increases if the possession occurs in the last 15 min of the match (6Q). However, when analyzing the SHAP values for the positive outcome "Goal," the probability increases between the 60th and 75th minutes of the match. This contradicts the findings from the 1999, 2003, and 2007 World Cups, where a higher number of goals were observed in the final 15 min of the match (Armatas et al., 2007), as well as the results from the most recent Women's Euro 2022 (Sanmiguel-Codina et al., 2025).

Additionally, the observation that starting an attack in the central lane (Start Zone Width = Central) increases the probability of success had not been noted in previous studies (Scanlan et al., 2020; Iván-Baragaño et al., 2021; Maneiro et al., 2022). This may suggest that while starting attacks from wide areas may facilitate successful entries into the penalty area, shots and goals are more likely to result from attacks initiated in central zones.

This study presents several limitations that should be addressed in future research. First, while the classification models achieved excellent performance on oversampled datasets using the SMOTE technique, their ability to detect true positives in the original dataset was notably poor. From a football perspective, this suggests that the actions leading to dangerous situations may follow highly specific patterns that generic classification models, such as Random Forest, are unable to effectively capture. In this context, future studies might benefit from the implementation of advanced statistical techniques like T-Patterns, which have proven effective in identifying offensive patterns and sequences in other sports (Pic and Jonsson, 2021; Pic et al., 2021). Additionally, exploring alternative tools to mitigate overfitting during model training is essential. Expanding the dataset by analyzing additional championships could also enhance the robustness of the identified patterns related to goal scoring. Furthermore, the inclusion of certain predictor variables, such as Match Outcome, was found to influence model performance, not due to their predictive capability, but because of their retrospective causal relationship (e.g., the winning team scored more goals). This introduces data leakage during model training. Consequently, future research should consider excluding such variables from the training process to ensure more reliable and generalizable results.

5 Conclusion

The models trained and tested in this study showed excellent performance on the resampled datasets using the SMOTE technique (Last et al., 2017). However, when these models were evaluated on the original dataset, their performance was low or non-existent. In the case of predicting Goals or Shots, the model achieved a recall of 13%, which slightly increased the relative frequency of the positive class but fell far short of an acceptable performance. For goal prediction, the model was unable to output the positive class at all. Based on this, it can be stated that such events in elite women's football possess very specific characteristics and patterns that cannot be clearly defined or that, at least, involve variables not analyzed in this study.

On the other hand, the SHAP explainability techniques applied in this study allowed for the identification of various variables associated with the achievement of goals and shots. Some of these variables showed similarities to previous studies, where success was categorized as entries into the penalty area or similar metrics. However, other variables such as start zone width, timing, or defensive intent had a significant influence on the model when analyzing a higher degree of success, enabling a tactical understanding of how these types of actions occur.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found in the article/supplementary material.

Author contributions

II-B: Data curation, Investigation, Methodology, Software, Supervision, Visualization, Writing – original draft, Writing – review & editing. AA: Formal analysis, Investigation, Supervision, Validation, Writing – review & editing. JL: Methodology, Writing – review & editing. RM: Conceptualization, Investigation, Supervision, Validation, Writing – original draft, Writing – review & editing.

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The principles of tactical formation identification in association football (soccer) — a survey

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This paper reviews the principles employed to identify team tactical formations in association football, covering over two decades of research based on event and tracking data. It first defines formations and discusses their history and importance. It then introduces the preprocessing and team/position-level principles. Preprocessing includes match segments and normalized locations followed by data representation using various options, such as average locations, hand-engineered features, and graphs for the team-level and relative locations, distributions, and images for the position-level approaches. Either of them is later followed by applying templates or clustering. Among the limitations for future research to address is the reliance on spatial rather than temporal aggregation, which bases formation identification on newly introduced coordinates that may not be available in raw tracking data. Assuming a fixed number of outfield players (e.g., 10) fails to address scenarios with fewer players due to red cards or injuries. Additionally, accounting for phases of play is crucial to provide more practical context and reduce noise by excluding irrelevant segments, such as set pieces. The existing formation templates do not support arrangments with more or fewer players in each horizontal line (e.g., 6-3-1). On the other hand, clustering forces new observations to be described with previously learned clusters, preventing the possibility of discovering emerging formations. Lastly, alternative evaluation methods should have been explored more rigorously, in the absence of ground truth labels. Overall, this study identifies assumptions, consequences, and drawbacks associated with formation identification principles to structure the body of knowledge and establish a foundation for the future.

KEYWORDS
football, soccer, formation, shape, position

Introduction

The success of the Roman Triplex Acies formation in ancient battles (1) and the power efficiency of migratory birds' V-shaped flight (2) are just two examples that demonstrate the benefits of collective behavior. Formations have also been studied in other domains, including transportation (3), robotics (4), space exploration (5), video games (6), choreography (7), and sports such as American football (8), field hockey (9), handball (10), and association football[1] (11).

In football, formations have been present since the early versions, as evidenced by available drawings from a festive match played in Italy in 1688, which depict team arrangements on the field, including players' defined distances (12). After the codification of football and its split from rugby in 1863, the first observed formations were 2-2-6, 1-2-7, and 2-3-5 (pyramid). Historically, formations have been modified to balance defensive and offensive capabilities while adapting to rule changes such as offside in 1925. Arsenal's 3-2-2-3 (W-M) from the 1930s, Brazil's 4-2-4 in the 1950s, and the 4-2-3-1 formation used in recent decades are a few examples of this continuous evolution (11) because there is no optimal formation as each has its pros and cons (13, 14).

We define "formation"[2] as an abstraction summarizing each team's spatial arrangement on the pitch over a match using labels (16) that are usually short to communicate useful and relevant information to the target audience in a consistent manner. While this definition means there is no requirement for a standard and unified set of these labels, they are commonly reported using three to five digits denoting the number of outfield players from defense to attack in each horizontal line[3] usually in a symmetric manner, like 4-4-2 (four defenders, four midfielders, and two attackers), as shown in Figure 1.

Formations can change in a match for various reasons (18) including the match score (19), coach instructions (20), substitutions (21), tactical position[4] switches, match phases (22–25), opponent (26), mental pressure, injuries, and yellow/red cards. This definition aligns with football as a dynamic interaction process (27) and contrasts with the traditional belief that formations are fixed throughout a match, as reported in "starting formation"[5] graphics in media and history books (11, 28).

Formations are important to ensure a team operates cohesively, without confusion or delay, while taking advantage of each player's abilities and conserving energy. Therefore, players' confidence is boosted and they can inflict maximum damage on their opponents while remaining less susceptible to attacks (1). Moreover, it serves as a reference (29) for players to remember their organization and responsibilities when distracted (30), helps

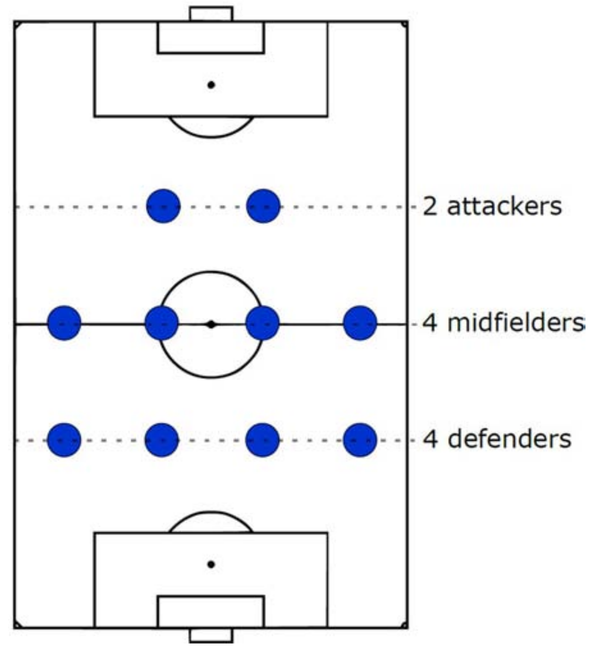

FIGURE 1
A (symmetric) 4-4-2 formation.

coaches reduce communication overhead, and shapes the team's collective behavior by creating desired scenarios (31), such as passing options and numerical superiorities. All these reasons could explain why formations are covered in coaching programs, interviews (22, 32–34), training sessions (20), dressing room discussions (35), and media (36).

Formations are also among the first considerations in opposition analysis (13, 20), as highlighted by the *spygate* incident (37). This is because coaches have the freedom to choose any[6] formation consisting of a goalkeeper and six to ten other starting players to counter opponents (11, 39–41). In addition, there are other factors that can influence a formation choice such as the skills of available players (19), tradition (11), recent results (42), coach and club's principles (43), league (30, 44), home or away (45), and pitch elevation (46).

Goal

Formation analysis is often carried out qualitatively (47) relying on previous matches using isolated observations (16), most seen arrangements (48), or only out-of-possession moments (49, 50) resulting in a time-consuming and subjective process (51). For instance, comparing the starting formations recorded by two industry data providers for the 2022 Men's World Cup shows

[1]Association/European football or soccer from hereafter is just referred to it as "football".

[2]The same term has also been used to describe the selection of the best team under specific constraints (15), which is not the subject of this paper. Therefore, we used "tactical formation" in the title to avoid this confusion. In this context, tactical does not mean intended formations but observed ones through data. Hereafter, we will refer to it simply as "formation".

[3]One can find exceptions where the emphasis is given to the vertical lines, as seen in 2-7-2 denoting the number of players from left to right (17). The digits in this case sum up to 11 as the goalkeeper is also considered.

[4]The term "tactical position", often communicated with labels such as center back and right midfield, typically refers to where players spend most of their match time on the pitch. Since "position" is also used in the literature for player locations (coordinates) from tracking data, we added the adjective "tactical" to avoid confusion.

[5]These graphics are analysts' educated guesses based on the starting players' list in addition to players' tactical positions and team formations from previous matches, as the team officials do not announce their formation.

[6]There is no restriction on the formation choice in the *Laws of the Game* (38).

only a 65% agreement (52, 53) highlighting the lack of ground truth formation labels (54).

To address these issues, dozens of data-driven studies have been conducted over the past decades to identify formations in a more automated, scalable, and objective manner. These solutions also can have player/coach recruitment in addition to performance and match analysis applications such as studying the relationship between formation choice and various success metrics (e.g., goals, expected goals, scoring zone entries) (30, 55, 56), examining the physical load implications of different formations (57–59), and comparing the identified formations with the instructed ones. Ideally, these approaches, given data availability, can also support real-time applications for media, fans, and specifically the coaching staff to facilitate in-game interventions.

Given the ongoing interest in this problem and the time required to get informed about the relevant developments and their limitations, we recognized the need for a survey on the subject of "formation identification principles in football using event and tracking data" to structure the body of knowledge, prevent redundant efforts, and establish a foundation for future research.

Method

Our survey is not a systematic review but rather an extensive overview of the principles used to identify football formations[7] using event and tracking data[8] in the past decades[9]. We put together similar attempts for each principle found in academic papers, presentations, books, theses, and patents starting with the seminal publications in football and their reference lists. Next, we monitored sources that cited the initial publications and subsequently expanded them to relevant principles from other sports and fields.

In summary, these principles are preprocessing the input data, followed by choosing either the team or position level. Regardless of the choice, there is a data representation and identification step followed up by evaluation. The goal at the team level is to directly report the formation for the entire team while the position level first starts by identifying individual player positions and then maps the set of those positions to a formation label using a pre-defined lookup table. Therefore, this survey also covers tactical position identification methods relevant to formation identification.

An overview of these principles and their concepts is depicted in Figure 2. Each step is explained through the remainder sections and subsections of this paper.

[7]Excluding studies focused on specific team segments, like defenders (60, 61).

[8]Excluding studies that relied on direct video or image analysis (62–65), as well as partial TV broadcast tracking data (66) because recent advances have allowed for generating full tracking data (67).

[9]The earliest attempts we found date back to the late 1990s in RoboCup and American football (8, 68).

Data

In this section, we introduce the event and tracking data sources. Event data is used only in "Match Segments" while tracking data is employed in all steps shown in Figure 2.

Event data

The event data commonly includes on-ball actions such as passes, throw-ins, shots, and fouls during a match, often with timestamps, locations, involved players, and other relevant attributes. The collection of event data can be traced back to the 1950s when Charles Reep began recording its basic elements occasionally with pen and paper (69). Today, event data is typically recorded by computer-assisted professional annotators (70).

Tracking data

The second source is the time series of the ball and player locations obtained through optical tracking cameras installed in the stadiums (71), radar-based systems such as Global Positioning System (GPS) sensors worn by players and inside the ball (72), or computer vision and deep learning models applied to TV footage (73). A tracking dataset with 25 frames per second results in more than three million records per match (74).

Preprocessing

In this section, the input data is preprocessed by transforming teams to have a consistent attacking direction (e.g., from bottom to top) to negate the effect of half-time side switches, or ignoring the goalkeeper locations, as they may not be relevant. Moreover, the pitch sizes are standardized since they can differ per stadium[10]. The other preprocessing tasks are explained in "match segments" or "normalized locations" subsections.

Match segments

Since formations can change throughout a match, as mentioned in the introduction, it is necessary to divide the match time into segments, known as phases of play, to report formations. For each phase, coaches instruct their teams to deploy a set of customized principles and arrangements (76, 77). While defining these segments is subjective, there are commonalities among the previous approaches seen in the literature, coaching textbooks, and match reports (78). For example, the England Football Association's training and

[10]However, the common pitch standardization methods result in distorted player locations (75).

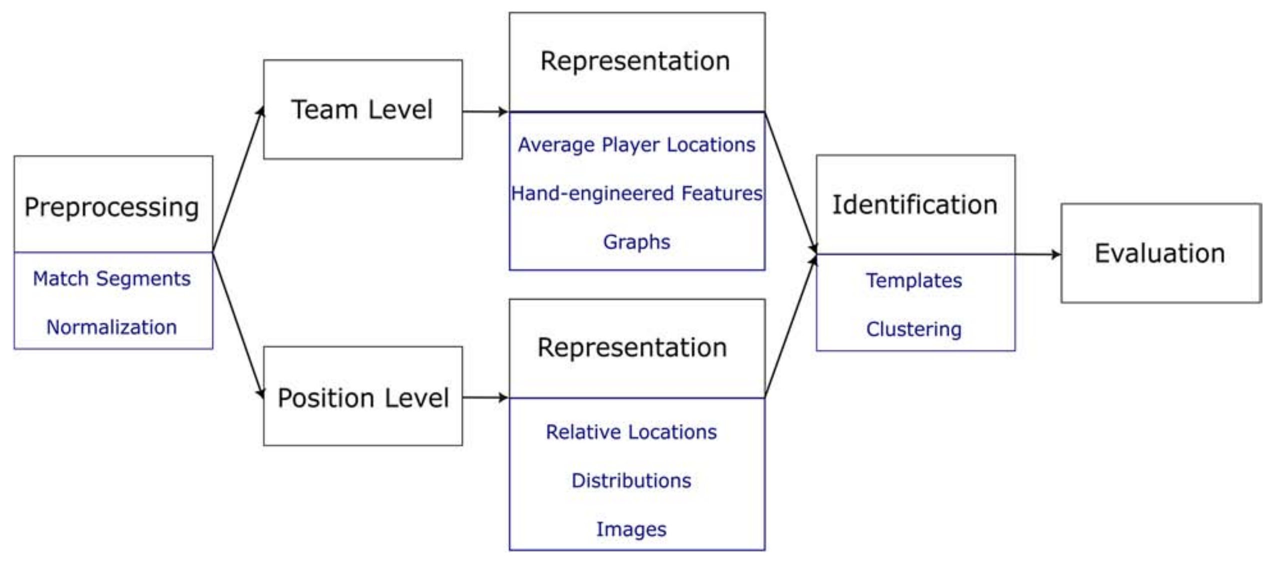

FIGURE 2
Overview of the formation identification principles.

coaching guide from 1967 introduced the attack (in-possession), defense (out-of-possession), and preparation (transition) phases (77). The transition phase can be divided into attack to defense and vice versa (79). Additionally, set-pieces are considered a separate phase by some coaches because a considerable proportion of goals comes from them (80).

One major difference among these approaches is how the in and out-of-possession phases are divided into smaller sub-phases. For instance, whether to base the division on when each of the opposite team's attack, midfield, and defense lines is broken (81) or to divide the pitch into tactical zones such as the first, middle, and last third of the field (20). This latter approach is reflected in the training grounds of some professional teams to guide player positioning and direction during training sessions (82).

To provide more context, formations should be reported per segment and previous studies operationalized it using a combination of event or tracking data:

1. Fixed time intervals, such as per match half (83) five-minute windows (84), and 15-minute windows subdivided in case of a substitution (85, 86).
2. In and out of possession sequences (25, 87) such as two-minute windows of each separately (88) with tweaks to discard interruptions, short sequences, and some seconds after throw-ins, free kicks, corners, and penalties (89) or consider only sub-windows bigger than five seconds to ignore transitions, and end the time window due to a substitution or half-time break (88).
3. Identification of common in and out-of-possession subphases such as build-up, and low/mid/high blocks using ball zone changes (90) or a Convolutional Neural Network (CNN) trained on labeled tracking data frame visualizations (55).
4. Change point identification by applying g-segmentation on Delaunay adjacency matrices (91), or planarity testing on the graph representation (92) to find distinct intervals (55, 93).

Match segments play a crucial role in identifying formations by excluding segments that have a different nature, such as set pieces. These aspects were overlooked in earlier attempts until recently (55). Additionally, these segments provide more context taking into account the team's arrangement concerning the opponent's influence and ball location, such as build-up (opposed/unopposed) (78). Analyzing segments will also allow one to discuss relevant sub-formations in each phase rather than focusing solely on the overall team arrangement. For instance, it is common to describe a team's build-up as 3–2 (three in the back and two in the middle).

Normalization

The objective here is to report formations regardless of their on-pitch location (89). For example, Figure 3 illustrates a 4-4-2 formation in various regions and to classify them as the same formation, certain studies have utilized one or both of the following steps, which are part of the Procrustes analysis (94), a statistical shape analysis method with a long history in biology (95).

In translation, the locations of each team's players are relocated with a constant vector (e.g., team centroid or common k-nearest neighbor[11]) to the pitch center (89, 93, 98, 99). To treat compact and narrow formations the same, scaling methods such as min-max (31, 89, 100), scaling to range (101), and division by standard deviation (45, 83, 91, 102–105) are employed.

However, it is crucial to mention that the normalization methods result in unintended transformations of player locations. For instance, applying min-max normalization to an unorthodox

[11]Inspired by players' alignments with nearest teammates (88, 96, 97).

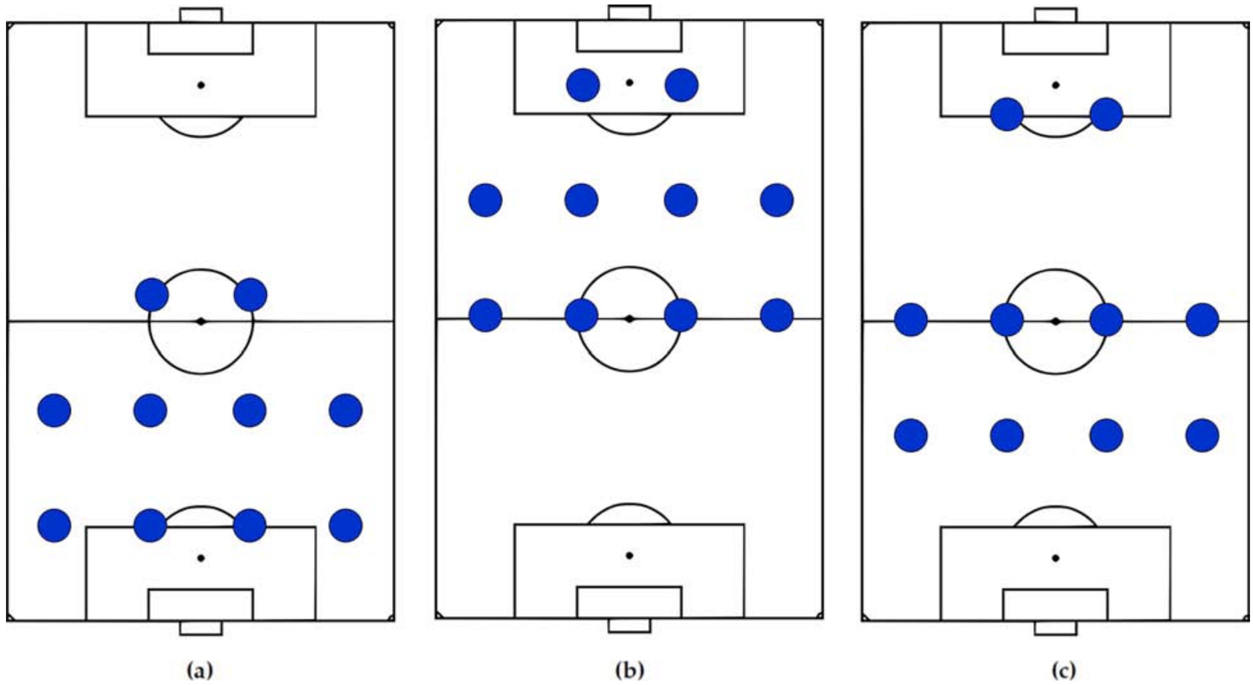

FIGURE 3
A 4-4-2 in defense **(a)**, attack **(b)**, and with two attackers playing higher up on the pitch **(c)**. All these arrangements should ideally be reported as 4-4-2. While the normalization step can handle **(a)** and **(b)**, it may result in reporting **(c)** as a different formation.

4-4-2, depicted in Figure 3c, where two attackers are located significantly higher up, may not achieve the desired outcome of categorizing it as the same formation as the other 4-4-2 formations shown in Figures 3a,b (106). Therefore, it is desired to achieve the same objective by the other pipeline steps.

Team level

Representation

The team-level formation representation should have the following properties:

1. Distinguishing Power: It should differ for distinct formations.
2. Uniqueness: The same formation should have a single and consistent representation.
3. Robustness: Small player location changes that do not alter the formation should not affect the representation.

In addition to the raw 2D coordinate vector (107), the following approaches have been proposed:

Average Player Locations is the simplest and most common representation (25, 85, 108, 109) in media and reports, as shown in Figure 4. However, a limitation of this representation is that compactness will be interpreted as a direct consequence of averaging. For instance, if a player switches from left to right during the first half, taking average locations per half would locate the player near the pitch center, which is not correct (25, 102) and results in misleading statements (110, 111). One possible mitigation is to compute averages over smaller windows. However, the appropriate time length will depend on the player's position change rate and remains unknown.

Hand-engineered Features where relevant indicators for formations such as team centroid, range (83), convex hull, spread, stretch (114), the distance between the farthest players (115), or team heatmaps (116) are computed. For instance, Figure 5 depicts an $n \times m$ grid placed around a team, resulting in an nm vector where a cell records the presence or absence of at least one player. The primary burden here remains the identification of relevant features.

Graphs representation assumes a set of relations (i.e., edges) among players that can describe their spatial organizations, seen through tracking data, by neighborhood structure rather than aggregated spatial distributions. For a team with n players, there are a maximum of $n(n-1)$ directed or $n(n-1)/2$ undirected relations ignoring self-loops, as shown in Figure 6a (118, 119). Since not all of these relations are relevant, previous studies applied heuristics to well-known graphs, such as minimum spanning trees, nearest-neighbor graphs (10, 92, 120–126), and Delaunay triangulation (DT) (104, 105, 127, 128)[12] to only consider neighborhood relations. Two examples of them are depicted in Figures 6b,c.

[12]In which players in adjacent Voronoi cells ("dominant regions") are connected (129, 130).

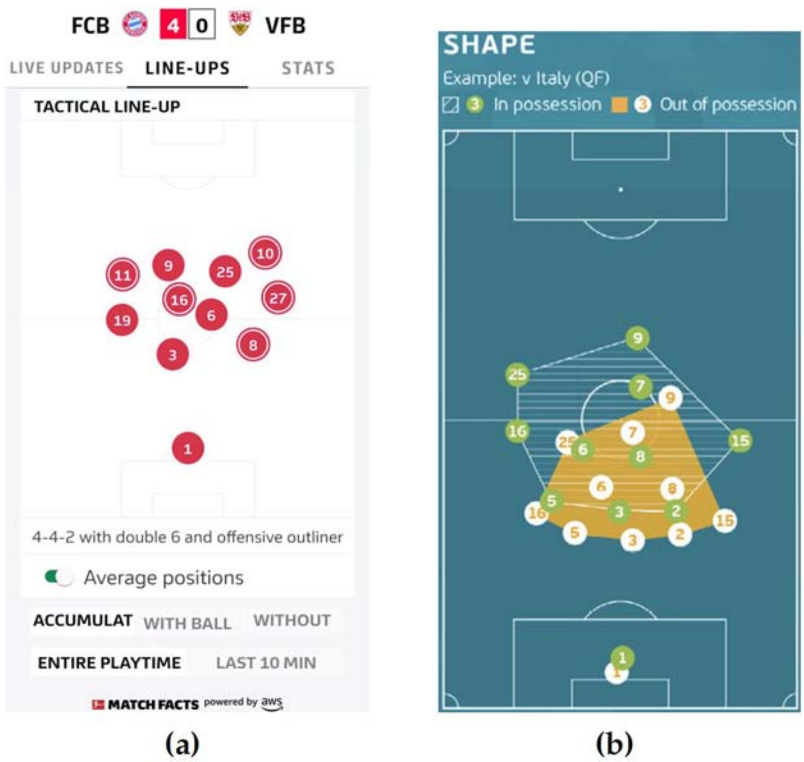

FIGURE 4
Examples of player average locations seen in the German Bundesliga's official mobile application (112) in (a) and UEFA's technical report (113) in (b).

These options have also been successful for similar applications in biometrics such as fingerprint (131–134), palmprint (135), and face identification (136). Additionally, these representations can incorporate inter-team and intra-team relationships when considering both teams together. Coaches have used similar graph representations as a tool for visual communication, too (137).

The primary obstacle lies in identifying the relevant relations. Tactical zones drawn on training grounds serve as just one reference for players to arrange themselves on the pitch and there are other references to consider, such as space (77), ball, goals (77), teammates and opposition players, field markings, nearest players (55), and passing options (77, 121). Moreover, some of these graph-based representations such as DT suffer from (1) a lack of a unique solution and (2) susceptible to minor player location changes, leading to errors in identifying the same formations and inconsistent results.

To the best of our knowledge, previously published formation studies did not consider addressing these two drawbacks when proposing graph-based representations.

Identification

To assign formations at the team level, both template-based and clustering approaches have been explored, as discussed below. Typically, formations are identified by matching frames or game segments to the most similar template or cluster. A more robust approach, inspired by match analysts' methods and overlooked by previous studies, involves using only frames or segments that exhibit 100% similarity with a template or cluster. Frames that do not fully align can be categorized as transitions, variations, or new formation labels based on similarity scores. Forcing non-perfect matches into predefined templates or clusters will introduce noise and obscure the results.

Templates are inspired by common labels like 4-4-2. This option involves preparing a list of formation templates and matching them to the most similar label. The matching process can be accomplished through similarity functions or machine learning algorithms.

Examples of similarity functions are Euclidean-based distances (83, 89, 138), graph edit distance (139), the Freeman code (140, 141), and the sum of element-wise differences divided by the maximal possible distance (84, 142, 143). Machine learning algorithms, such as neural networks, support vector machines, and decision trees, are also employed in some of those attempts (100, 107, 115, 117, 144–150).

One difficulty here is maintaining a consistent and up-to-date list of these templates because of (1) differences across the sources and (2) emergence of new formations over time. For example, Table 1 shows the formations listed by three well-known industry

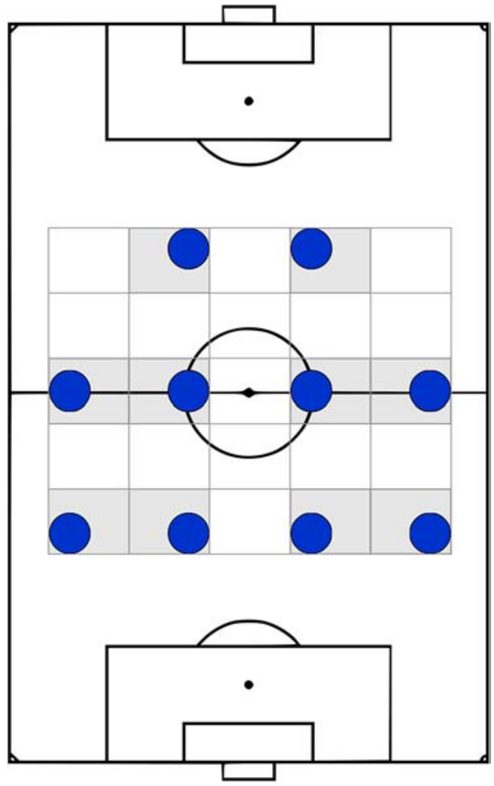

FIGURE 5
A 5 × 5 grid, inspired by (117), with gray cells indicating the presence of at least one player. This produces a vector of length 25 (5 × 5) to represent the team's arrangement.

data providers (52, 151, 152). The matching agreement among these providers is just 30% (13 out of 44). This comparison highlights the subjective nature of these labels. Additionally, the FIFA video game series offers 52 formations (153), providing variations to the same label, such as 4-4-2 flat and holding, because players can be arranged in different ways while still using the same label (20).

A notable observation about these predefined formation templates is their symmetry, as seen in Figure 1 and coaching documents reported before. However, this assumption appears unrealistic when it comes to player arrangements observed through tracking data.

Clustering avoids the difficulties explained in the template-based option and is not restricted to a set of predefined labels. It focuses on learning formations directly from tracking data by inferring the number of players in each horizontal (i.e., defense, midfield, and attack) or vertical (flank) line directly, as shown in Figure 1. Various clustering algorithms, such as complete-linkage (154), K-means (92, 155, 156), Jenks natural breaks optimization & (157), Percentage (101), FOREL (158), and team width/length-based (159), have been proposed to cluster players' x and y coordinates separately per frame. The number of lines can be determined by setting a fixed number (e.g., three) or using optimization methods like the elbow or silhouette method.

Position level

Several studies focused on reporting team formations bottom-up by starting from smaller units called positions[13], which are defined based on where on the pitch players spend most of their match time. Positions are commonly communicated with labels such as center back and right midfield, as shown in Figure 7, for an example.

The reason behind considering positions rather than player identifiers is that players can swap positions, be substituted or sent off during a match, or differ across matches while the set of all possible positions on the pitch remains fixed. Similar to the team-level approach, an appropriate data representation is chosen and later either template or clustering is applied to identify positions. The key assumption employed in the position-level approach is that no two teammates can occupy the same position simultaneously (9). Therefore, a one-to-one mapping is applied to assign either a template or cluster position by solving the assignment problem (161).

Similar to Table 1, we compiled the list of position labels from the same three industry data providers see Table 2 by merging labels with identical descriptions or spatial arrangements on the pitch. This comparison shows a 79% agreement, indicating a stronger consensus than for formations.

Representation

Player position data representation proposals apart from the 2D coordinate vectors can be classified into the following categories:

Relative Locations are based on how position labels have been named relative to each other. For instance, a left back in a 4-4-2 formation is located to the left of the center backs (45). This approach describes a position using statistics relative to the other players (8) such as the percentage of teammates located in the front, behind, right, and left angle bins (83), as depicted in Figure 8a, the division into 16 instead of four (162, 163), or the amount of created angles (50, 164).

Distributions such as bivariate normal distributions (88) and normalized heatmaps containing players' occupancy probabilities (83, 165), as shown in Figure 8b.

Images can capture a position's spatial arrangement, as proposed in (99) and shown in Figure 8c to serve as input for image classifiers.

Identification

Similar to the team level, the position-level identification approaches are templates and clustering.

[13]Some use the term "role" to refer to the position (87, 91, 160).

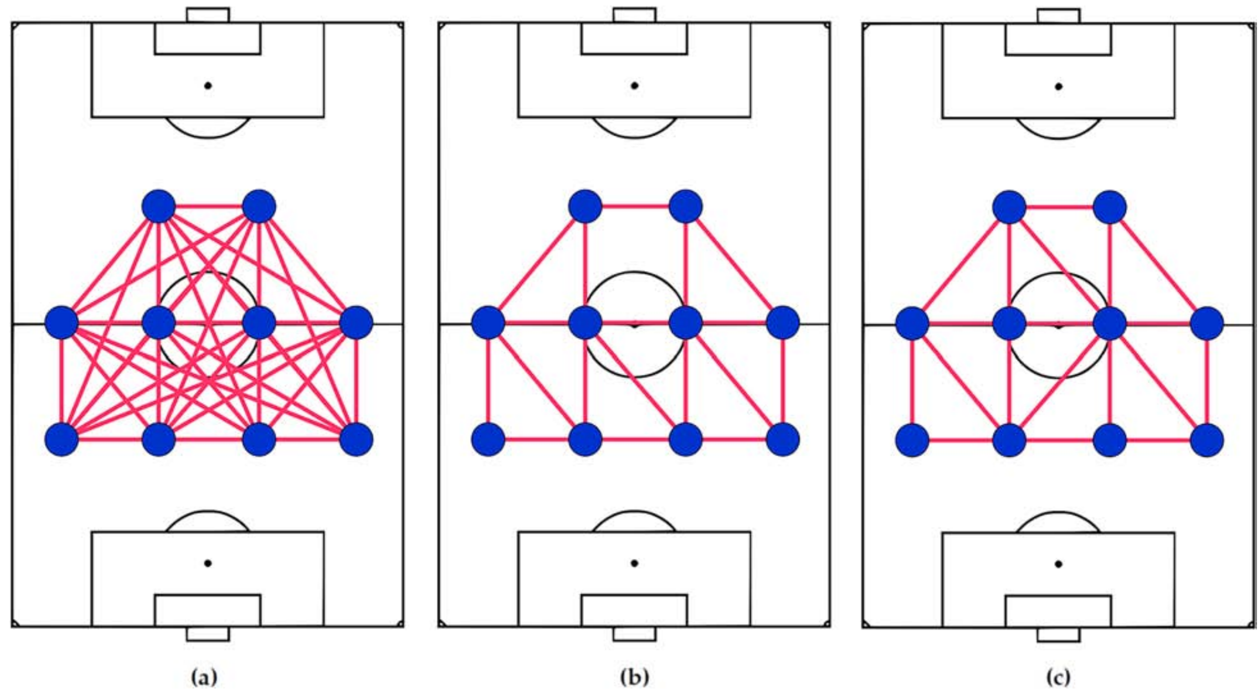

FIGURE 6
A 4-4-2 representation as a complete undirected graph (a), a union of minimum and second minimum spanning trees (b) presented in (82), and delaunay triangulation (c) proposed in (104). Considering the properties a team-level representation should have, a complete graph (a) can't distinguish formations since all players are connected. The algorithms producing (b) and (c) do not guarantee a unique answer and are not robust against small player location changes that don't affect the team's formation.

Templates ensure adherence to common position labels. This approach assigns the representation to a predefined set of position templates using one of the following methods:

1. **Rule-based** such as defining arbitrary pitch regions (home areas) for each position. When a player moves outside the designated area, the position is updated accordingly (166, 167).
2. **Similarity functions** such as Chi-square distance for the relative locations representation and naive Bayes as a distance function on the log probabilities of the heatmaps (83).
3. **Machine learning algorithms** such as ResNet on images of color-coded positions, see Figure 8c (99).

The issues discussed for the template-based approach at the team level are also valid here.

Clustering moves away from the template issues and various clustering algorithms (78) such as k-means (9, 31, 45, 51, 83, 87, 102, 168–171), Gaussian mixture models (25, 103, 172–175), and hierarchical agglomerative (25, 55, 88, 91, 96, 97, 104, 175–179) have been applied. To determine the number of position clusters, different numbers of clusters (87), dendrogram (88, 105), or a combination of them along with video/match analysts' inputs were considered (55).

Evaluation

Regardless of the approach, previous studies have generally fallen short in terms of reporting their accuracy, execution time, and required storage. This is understandable given the variations in validation datasets, evaluation metrics, labeling quality, granularity, and expert interpretations (106).

While quantitative evaluation in this area remains difficult due to the lack of ground truth in sports analytics (180), there are other aspects to an evaluation, as suggested for mathematical models in general and sports analytics ones in particular (181, 182). We divide them into design and qualitative categories.

In design, aspects such as realistic assumptions, output robustness to small input data changes, output stability over time, reproducibility, and interpretability can be covered. In the qualitative category, one can address whether the outputs behave as expected in known and boundary scenarios and if the results are intuitive, insightful, and actionable for practitioners (183).

Discussion & conclusion

While the definition of formations remains an ill-defined problem, we aimed to provide more clarity by defining them as the spatial arrangement of players on the field. Our paper offers an overview of more than 20 years of research on team tactical formations starting from the late 1990s in simulated robotic soccer and American football. The importance of formations is highlighted through opposition analysis, training sessions, and media coverage and the formation identification still is carried

TABLE 1 Comparison of three data providers' 44 formations shows 30% agreement (colored rows).

Formation	StatsBomb	Wyscout	Stats Perform
3-1-2-1-1-2	×		
3-1-2-2-2	×		
3-1-4-2	×		×
3-1-5-1			×
3-2-1-2-2	×		
3-2-2-2-1	×		
3-2-3-2	×	×	
3-2-4-1			×
3-3-3-1		×	×
3-3-2-2			×
3-3-1-3			×
3-3-4			×
3-4-1-2	×	×	×
3-4-2-1	×	×	
3-4-3	×	×	×
3-5-1-1	×	×	
3-5-2	×	×	×
3-6-1			×
5-1-2-1-2			×
5-1-2-2			×
5-1-3-1			×
5-1-4			×
5-2-2-1	×		×
5-2-1-2			×
5-2-3			×
5-3-2	×	×	×
5-4-1	×	×	×
4-1-1-3-1	×		
4-1-2-1-2	×		×
4-1-2-2-1	×		
4-1-3-2	×	×	×
4-1-4-1	×	×	×
4-2-1-2-1	×		
4-2-1-3	×	×	
4-2-2-1-1	×		
4-2-2-2	×	×	×
4-2-3-1	×	×	×
4-2-4			×
4-3-2-1	×	×	×
4-3-1-2	×	×	×
4-3-3	×	×	×
4-4-1-1	×	×	
4-4-2	×	×	×
4-5-1	×	×	×

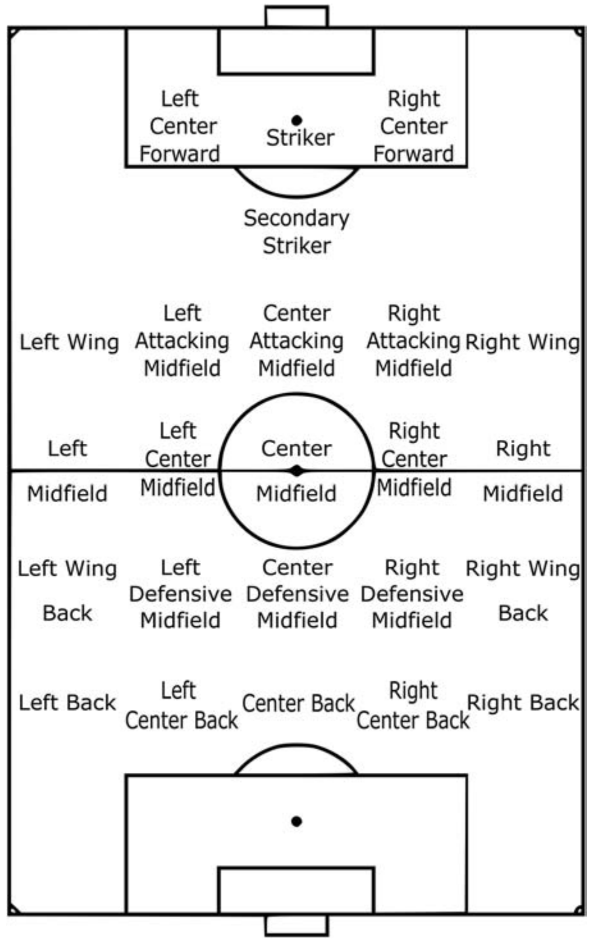

FIGURE 7
The outfield tactical position locations documented by StatsBomb (52).

out qualitatively to a large extent by counting the number of players in each horizontal line overlooking the vertical disposition.

The main principles were structured as first preprocessing and later taking either a team or position-level approach. The two main concepts employed in the preprocessing step were match segments and normalized locations. The objective of dividing the match time into smaller windows, known as phases of play, is to move beyond reporting one fixed formation for the entire match. Normalized locations aimed to report the same formation for the same arrangements, regardless of where they occurred. However, the potential unintended consequences were not fully understood. Moreover, the same objective can be achieved through other steps of the pipeline without the need for normalization.

After preprocessing, two different paths were followed: The team-level approach looks at a whole team at once while the position level starts with positions as smaller units to build on. In both, the first step is data representation and later, the detection using either qualitatively labeled data (templates) or clustering methods.

Among the data representation options, average locations were the simplest and most commonly used. However, they lead to misleading statements due to the natural outcome of compactness resulting from averaging. When utilizing hand-engineered features or graph representations, it is crucial to carefully select the elements to include in those representations. These elements should align with the references coaches use to instruct team arrangements. Additionally, the representation should be unique for the same arrangements, or arrangements that are not distinguishable due to small player location differences.

After data representation in the team or position levels, formation identification has been achieved by employing domain knowledge through templates or relying on data through

TABLE 2 Comparison of three data providers' 24 outfield positions shows 79% agreement (colored rows).

Position	StatsBomb	Wyscout	Stats perform
Right Back	×	×	×
Right Center Back	×	×	×
Center Back	×	×	×
Left Center Back	×	×	×
Left Back	×	×	×
Right Wing Back	×	×	×
Right Defensive Midfield	×	×	
Center Defensive Midfield	×	×	
Left Defensive Midfield	×	×	
Left Wing Back	×	×	×
Right Midfield	×	×	×
Right Center Midfield	×	×	×
Center Midfield	×		×
Left Center Midfield	×	×	×
Left Midfield	×	×	×
Right Wing	×	×	×
Right Attacking Midfield	×	×	×
Center Attacking Midfield	×	×	×
Left Attacking Midfield	×	×	×
Left Wing	×	×	×
Secondary Striker	×		×
Right Center Forward	×	×	×
Striker	×	×	×
Left Center Forward	×	×	×

clustering. While templates are relatable to public understanding and can be widely accepted, preparing a list of labels and qualitatively assessing them could be cumbersome, especially since there is no worldwide consensus and they change over time. This could be why some adopted clustering to bypass the issues associated with templates. Clustering avoids these issues but on the other hand, requires tracking data of a large number of matches and will limit the future observations to be mapped to one of the existing formation clusters seen in the selected set of matches.

Since our comparison has shown more consensus in position labels than formations, we suggest carefully considering match segments and choosing the position-level approach. For data representation, a graph choice seems reasonable because it can achieve the objectives of the normalization step without facing its drawbacks. When deciding between templates or clustering, it is important to consider the drawbacks of each.

The limitations identified in each step were documented in their respective sections and Table 3 highlights the major ones. Future research can address these limitations and then provide the most value by reporting identified formations and player tactical positions over match time, incorporating contextual factors such as phases of play, substitutions, red cards, scoreline, halftime, and stoppage breaks to reveal formation and position dynamics. Finally, large-scale studies could identify patterns

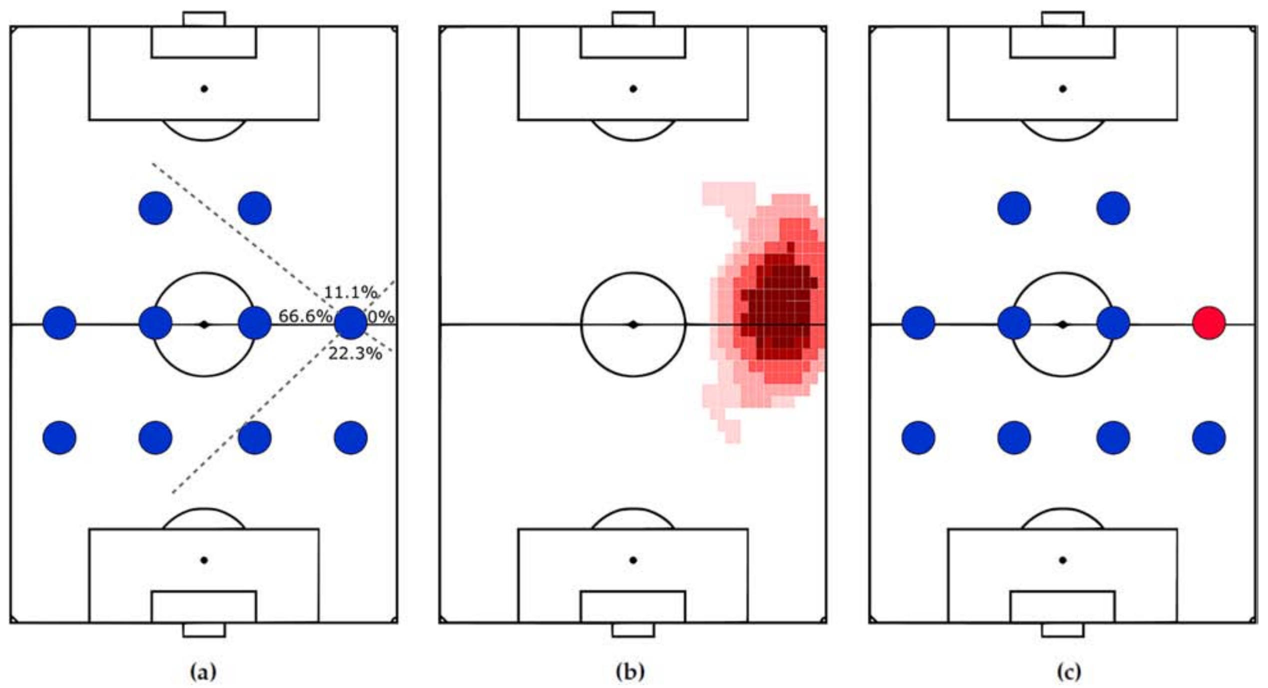

FIGURE 8
A right midfielders' representation using relative locations (a), heatmap (b), and color-coded image (c).

TABLE 3 Some recognized limitations of previous studies.

Limitation	Description
Spatial Aggregation	Introduces coordinates not present in tracking data, as noted in normalization.
Ignoring Phases of Play	Mixes irrelevant coordinates, such as those from set pieces, into results.
Fixed Number of Players	Does not account for scenarios with fewer players due to suspensions or injuries (184).
Existing Pre-defined Templates	Lack flexibility for formations with fewer or more players in each horizontal line (e.g., 6-3-1), see Table 1.
Clustering	Requires extensive tracking data and constrains new observations to predefined clusters, failing to recognize emerging formations.
Forced matching	Assigns a formation to each match frame by selecting the most similar (lowest distance) template or cluster. Instead, one could adopt the approach of match analysts, who focus only on moments with 100% similarity to a formation template or cluster and consider all others as transitions.
Evaluation	Usually is neglected or limited to accuracy-related metrics with an insufficient number of classes. However, those are not applicable in this context due to the lack of ground truth labels (54) and alternative methods, outlined in the evaluation section, should be considered.

across leagues, seasons, coaches, and teams, as well as how formations counter each other, considering relevant success factors. These advancements will also significantly influence sports science studies that focus on physical load monitoring.

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HS: Writing – original draft, Writing – review & editing.

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Conflict of interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that Generative AI was used in the creation of this manuscript. As stated in the acknowledgment section, ChatGPT 3.5 is only used for cohesive and concise text revision and nothing else.

Publisher's note

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Performance analysis using the classification composition and match records in wheelchair basketball matches

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Introduction: This study provides essential information for wheelchair basketball coaches and players to enhance tactical applications and training for improved performance. By examining the latest trends in sports classification and performance factors influencing game outcomes, this study presents a comparative analysis across different levels of international wheelchair basketball play.
Methods: To achieve this objective, major game factors were examined by analyzing descriptive statistics from each year regarding recent trends in sports class composition and the playing time of each class, followed by group difference tests. A total of 209 official game records from 24 teams participating in major international wheelchair basketball tournaments were analyzed. Group differences were tested in terms of sports class composition, playing time, and performance metrics.
Results: First, scoring factors directly affecting game results were compared between groups. The difference test showed that the success rates of 2-point (50.73%) and 3-point (31.41%) shots differed significantly, while the free throw success rate did not. Significant differences were also found in the number of assists (22.94), defensive rebounds (27.38), and steals (5.95). Second, the medal group was compared with the non-medal group. The average sports class composition per quarter was significantly higher in the medal group (1QSC: 14.00, 2QSC: 13.96, 3QSC: 13.98, 4QSC: 13.96) than in the other group (1QSC: 13.89, 2QSC: 13.89, 3QSC: 13.85, 4QSC: 13.88). In terms of playing time differences by class, medal group players showed longer participation: 2.5-point (22:21), 4.0-point (14:46), 3.0-point (19:05), and 1.5-point (16:15). Third, from 2012 to 2022, trends in sports class composition and quarterly playing time have evolved. In 2022, the average playing time of 1.5-point and 4.0-point athletes decreased by about 4 min compared to 2012, while the playing time of 4.5-point athletes increased by approximately 5 min and that of 3.0-point athletes increased by about 2 min.

KEYWORDS
wheelchair basketball, performance, classification, para sports, trend analysis, team sports

1 Introduction

Wheelchair basketball (WB) is one of the most popular official events in the Paralympic Games (PG). Since 1964, when it was selected as an official game event at the Tokyo PG, WB has spread worldwide for over 60 years. Furthermore, the PG are held quadrennially, while world championship games (WC) and regional international competitions continue to be held under the supervision of the International Wheelchair

Basketball Federation (IWBF) to encourage para-athletes to participate and compete to achieve their potential.

From 2012 to 2022, about 27 countries participated in the WC and PG of WB. As of 2024, members of the IWBF include 24 in Africa, 21 in America, 28 in Asia and Oceania, and 36 in Europe, with about 289 players from 109 countries. Wheelchair basketball leagues are actively conducted around the globe, including Europe, North America, Asia, and so forth (1).

As WB events have become common and developed, para-athletes' personal skills and team performances in WC and PG have improved significantly. As a result, global competitiveness is intense, with more diversified strategies required more than ever before in preparation for each competition (2).

Basketball games have a fast transition between offense and defense, requiring fast and delicate judgment because the game result may be changed within seconds. To secure winning and outstanding team performance, the optimized team of players is organized for each game (3). Particularly in contemporary basketball, roles are divided explicitly among 5 players for specific strategies and tactics, which definitely decide the victory and defeat of the game. An athlete's skill is essential in team sports, but the team's organization and tactics are also vital to winning (4–6).

Similarly, in WB, player selection can factor in winning. Still, due to the "Sports Classification System", it has to be organized differently than in basketball. In particular, due to the decreasing number of international competition games and changes in the classification of para-athletes, the major national teams (the United States of America, Great Britain, Australia, etc.) are no longer relying on individual performance but on team cohesion and tactics to win matches. Furthermore, the overall trend of principal countries is to select the national team by identifying the appropriate combination of players and the sum of their classifications to maximize performance and teamwork. In other words, to formulate a strategy, match analysis of WB needs to assess the match factors that affect the match results, and the factor analysis related to each player's sports class points as a significant part of the team performance characteristics (5).

In general, basketball playing styles and roles change depending on international trends and training methods (7). For example, Štrumbelj et al. (8) points out that ever since 2001, when the shot clock changed from 30 s to 24 s, the numbers of team offenses, earning scores, and two-point shots have increased during the 10 seasons, whereas the number of 3-point shots has decreased. As the number of three-point attempts in international basketball increased in 2010, and as offensive and defensive transitions became faster, teams have demanded players to attack using space and defend in various patterns (9). Players are given multiple roles, and many different training methods are applied flexibly in line with international trends.

Similar to the changes in basketball mentioned above, WB has also seen changes in the rules and how the game gets played. For example, the sports classification in WB was changed to the evidence-based form in the 2016 Rio PG, and the new minimum impairment criteria were applied in the 2021 Tokyo PG. Factors affecting sports performance in para sports include participants' classification, health condition, and training method, among which classification factors vary significantly by a player's function. Therefore, understanding the sports classification factors and playing time among countries known for the central team's performance will be vital in deciding strategies.

Although such research is not relatively active in WB, the game operation is similar to that of ordinary basketball. Thus, strategies may be established based on similar analytic approaches for game performance improvement. Previous studies in WB focused on physical abilities and analyses of victory and defeat based on team records (10–13).

Additionally, sports class factors, a deciding characteristic for WB, are significant elements in analytic approaches for game performance improvement. However, previous studies on the sport class of WB focused on kinematics and differences in skills and physical functions related to each player's points in terms of sports medicine (14–18). As in previous studies, such analyses on individual players' physical functions and abilities have limitations in understanding major factors affecting WB game performance.

Given the limitations of previous research, as mentioned earlier, the association among sports performance, sports-class composition (classification), and match results need to be investigated. In previous studies, variables other than sports-class and playing time (offense, defense, turnovers, etc.) were used to analyze the difference in performance between the top and bottom groups (13, 16). However, since WB limits the number of points that can be played (within 14 points) to minimize the type of impairment that affects performance, it is important to compare the combination of points and playing time per quarter for each group. In addition, as of the Rio PG, the International Paralympic Committee introduced an evidence-based classification for each para sport (19), and some of the classes were adjusted in wheelchair basketball, which resulted in a tendency for the number of points to fluctuate. For this reason, this study aims to analyze the key factors influencing WB performance by examining national performance characteristics and the composition of sports classes, dividing players into high- and low-performing groups based on official records from central international men's WB competitions, by diagnosing the primary variables and identifying trends in sports class composition and performance factors.

Ultimately, this study provides essential information for WB coaches and players to enhance tactical application and training for improved performance. By examining the latest trends in sports classification and the performance factors that impact game outcomes, this study will present a comparative analysis across different levels of play in international WB.

2 Method

2.1 Data collection

This study analyzes the changes in "sport classification composition" and "playing time by classification" between high-performing and non-high-performing groups in WB. As the sport undergoes changes due to the recent application of evidence-based classification led by the IPC, the analysis explores key competitive variables to identify emerging trends.

To analyze the performance details of international wheelchair basketball games, this study selected the official records of 209 games among 24 teams that participated in major international wheelchair basketball games from August 30, 2012, to June 20, 2023 ($n = 418$). To achieve the objectives of this study, data were collected from the IWBF WC and PG held in London (2012) and Rio (2016) before the introduction of evidence-based classification, as well as from the IWBF WC and PG after the introduction of this classification. Additionally, as most research on the IWBF's rules and classification has been conducted since the 2010s, score sheets from the 2010 Games were likewise collected.

This study gathered data from publicly official records on the IWBF's website (https://iwbf.org/, accessed on 12 March 2024). Furthermore, the researcher obtained the sports class composition for each quarter through videos on the IWBF and FIBA's official websites and YouTube. However, as shown in Table 1, the researcher removed those that did not have uploaded videos or did not accurately display the official results.

2.2 Data processing

First, descriptive statistics analysis was performed on collected match records with calculated average and standard deviation. To understand the differences between the groups that determine the level of competition in sports, this analysis distinguished between countries that won medals in each sport and those that did not. Medal-winning countries are fewer in number in each competition, but they represent superior performance and inspire other countries regarding strategy and tactics.

Second, the non-parametric statistics technique, "Mann–Whitney *U*-Test", was performed to verify differences in the match results, sports class composition, and playing time (see Table 2) using the IBM SPSS 27.0 program. The Mann–Whitney *U*-test is a non-parametric test that compares the means of samples with the same population characteristics and determines the difference between two sample means (20). In this study, the

TABLE 1 Number of 2012–2022 WC and PG.

Event	Number of games	Remark
2012 London PG	38	Not uploaded 6 games
2016 Rio PG	42	
2018 Hamburg Wheelchair Basketball WC	41	Not uploaded 7 games
2020 Tokyo PG	41	Not uploaded 1 games
2022 Dubai Wheelchair Basketball WC	47	Data missing 6 game
Total	209	

TABLE 2 Research subjects and variables.

Subjects	Variables	Subjects	Variables
1QSC	1st quarter Sport Class Composition	2PA	2-Points Attempt
2QSC	2nd quarter Sport Class Composition	2P%	2-Points Shooting Percentage
3QSC	3rd quarter sport class Composition	3PM	3-Points Made
4QSC	4th quarter sport class Composition	3PA	3-Points Attempt
1.0 played minutes	1.0-point player played minutes	3P%	3-Points Shooting Percentage
1.5 played minutes	1.5-point player played minutes	FTM	Free Throw Made
2.0 played minutes	2.0-point player played minutes	FTA	Free Throw Attempt
2.5 played minutes	2.5-point player played minutes	FT%	Free Throw Percentage
3.0 played minutes	3.0-point player played minutes	OR	Offensive Rebounds
3.5 played minutes	3.5-point player played minutes	DR	Defensive Rebounds
4.0 played minutes	4.0-point player played minutes	TOT	Total Rebounds
4.5 played minutes	4.5-point player played minutes	AS	Assists
PTS	Points	TO	Turnovers
FGM	Field Goals Made	ST	Steals
FGA	Field Goals Attempt	BS	Block Shots
FG%	Field Goals Shooting Percentage	PF	Personal Fouls
2PM	2-Points Made		

Mann–Whitney *U*-test was applied to identify nonparametric differences in the number of medal-winning and non-medal-winning countries participating in the International Wheelchair Basketball Games and to identify nonparametric differences in the outcomes of competitions and the classification between groups. Since the difference in number between the medal group and the other group was significant and the basic assumption of parametric statistics (normality test) failed, the non-parametric statistics method was applied instead. The statistical significance level was set to.05.

Third, trends were analyzed in international wheelchair basketball games each year. Game trends were analyzed based on the descriptive statistics of annual match records. Specifically, trend analysis is used to identify the records of para-athletes and teams to check the performance contents of national athletes and to set target standards to promote performance in international sports competitions (19). Therefore, the trend information applied in this study can be used to compose the WB line-up and training by checking trends in the performance of principal countries in international wheelchair basketball competitions.

3 Results

3.1 Descriptive statistics

Descriptive statistics are presented in Table 3. As for results depending on the sports classes, sports classes competing in each

TABLE 3 Descriptive statistics on game (2012 to 2022).

Variables	N	Mean	SD	Variables	N	Mean	SD
1QSC	418	13.92	.224	2PA	418	52.35	7.353
2QSC	418	13.91	.228	2P%	418	46.71	9.127
3QSC	418	13.88	.280	3PM	418	1.86	1.637
4QSC	418	13.90	.280	3PA	418	7.61	4.344
1.0 played minutes	408	17:44	7:44	3P%	418	24.24	20.229
1.5 played minutes	250	18:53	8:53	FTM	418	7.09	4.284
2.0 played minutes	291	17:46	9:25	FTA	418	12.35	6.627
2.5 played minutes	290	18:47	9:43	FT%	418	55.74	19.522
3.0 played minutes	347	21:12	9:27	OR	418	8.22	3.719
3.5 played minutes	264	15:02	9:54	DR	418	26.22	5.440
4.0 played minutes	356	16:52	9:08	TOT	418	34.44	6.790
4.5 played minutes	339	17:55	8:44	AST	418	19.61	6.025
PTS	418	61.94	15.034	STL	418	5.13	3.162
FGM	418	26.50	6.585	BLK	418	0.85	1.140
FGA	418	59.94	6.544	TO	418	12.25	5.397
FG%	418	43.99	9.000	PF	418	15.60	4.602
2PM	418	24.64	6.511				

TABLE 4 Difference test depending on the quarterly sport class composition and playing time in groups.

Variables	Medal group		Non-Medal group		Mann–Whitney *U*	Sig
	Mean	SD	Mean	SD		
1QSC	14.00	.001	13.89	.255	13788.500	.001***
2QSC	13.96	.183	13.89	.241	14873.500	.003**
3QSC	13.98	.118	13.85	.310	13382.000	.001***
4QSC	13.96	.155	13.88	.309	14841.000	.004**
1.0 played minutes	16:37	7:53	18:08	7:39	14693.500	.152
1.5 played minutes	16:15	7:11	19:21	9:05	3106.000	.025*
2.0 played minutes	17:51	8:59	17:45	9:36	8193.000	.858
2.5 played minutes	22:21	9:21	16:49	9:24	6620.500	.001***
3.0 played minutes	19:05	11:19	22:04	8:27	9704.000	.002**
3.5 played minutes	14:55	8:08	15:05	10:29	6499.000	.522
4.0 played minutes	14:46	10:09	17:38	8:37	9652.500	.001***
4.5 played minutes	17:34	7:32	18:03	9:08	10748.500	.503

*$p < .1$.
**$p < .05$.
***$p < .01$.

quarter were given almost 14 points. The playing time of each sports class was 17:44 min for players of 1.0 points, 18:53 min for players of 1.5 points, 17:46 min for players of 2.0 points, 18:47 min for players of 2.5 points, 21:12 min for players of 3.0 points, 15:02 min for players of 3.5 points, 16:52 min for players of 4.0 points, and 17:55 min for players of 4.5 points. In general, players of 1.5 points, 2.5 points, and 3.0 points were given longer playing time than others. In a review of game results, the average score of each game was 61.94. The successful field shots and attempts were 26.50 and 59.94, respectively. The successful 2-point shots and attempts were 24.64 and 52.35, respectively. The successful 3-point shots and attempts were 1.86 and 7.61, respectively. The successful free throws and attempts were 7.09 and 12.35, respectively. The offense rebounds and defense rebounds per game were 8.22 and 26.22. The assists, steals, block shots, turnovers, and errors were 19.61, 5.13, 0.85, 12.25, and 15.60, respectively.

3.2 Difference test

3.2.1 Composition and playing time by sports class between groups

The second set of research findings is about the difference in match records between the groups from 2012 to 2022 in Tables 4, 5. Given the difference in test results between groups, particularly regarding the sport class, the medal group showed a higher level of points in the average quarterly rating (1Q: 14 points, 2Q: 13.96 points, 3Q: 13.98 points, 4Q: 13.96 points) than the other group (1Q: 13.89 points, 2Q: 13.89 points, 3Q: 13.85 points, 4Q: 13.88 points), and the difference was significant. In addition, the playing time depending on the points of the medal group was as follows: 2.5 points (22:21), 3.0 points (19:05), 2.0 points (17:51), 4.5 points (17:34), 1.0 points (16:37), 1.5 points (16:15), 3.5 points (14:55), and 4.0 points (14:46) in order. That of the other group was as follows: 3.0 points (22:04),

TABLE 5 Difference test on game results in groups (2012 to 2022).

Variables	Medal group		Non-Medal group		Mann–Whitney *U*	Sig
	Mean	SD	Mean	SD		
PTS	69.75	10.490	59.28	15.453	9700.500	.001***
FGM	30.01	4.715	25.29	6.725	9409.000	.001***
FGA	61.83	5.918	59.28	6.645	13034.500	.001***
FG%	48.58	6.293	42.42	9.278	9858.500	.001***
2PM	28.07	4.852	23.46	6.612	9464.500	.001***
2PA	55.35	6.102	51.30	7.462	11582.000	.001***
2P%	50.73	6.747	45.33	9.462	10927.000	.001***
3PM	1.93	1.500	1.83	1.687	15951.000	.401
3PA	6.49	3.697	8.01	4.482	13514.000	.002**
3P%	31.41	23.393	21.72	18.399	12586.500	.001***
FTM	7.79	4.436	6.86	4.210	14804.000	.060
FTA	12.95	6.536	12.17	6.660	15681.000	.284
FT%	57.64	17.788	55.17	20.061	15149.000	.118
OR	8.35	3.550	8.16	3.781	16398.000	.682
DR	27.38	5.286	25.83	5.456	13988.000	.008**
TOT	35.73	5.952	33.99	7.031	13906.000	.007**
AST	22.94	4.956	18.47	5.948	9525.000	.001***
STL	5.95	3.937	4.84	2.806	14242.000	.016*
BLK	1.04	1.380	.79	1.040	15390.000	.148
TO	9.40	3.701	13.22	5.552	9958.500	.001***
PF	13.98	4.937	16.17	4.343	12346.000	.001***

*$p < .1$.
**$p < .05$.
***$p < .01$.

TABLE 6 The quarterly sport class composition trend and playing minutes from 2012 to 2022.

Year	2012		2016		2018		2020		2022	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1QSC	13.95	.247	13.92	.187	13.89	.261	13.96	.141	13.89	.253
2QSC	13.99	.081	13.92	.198	13.90	.269	13.90	.219	13.87	.286
3QSC	13.94	.182	13.91	.193	13.85	.280	13.90	.228	13.83	.412
4QSC	13.95	.193	13.90	.277	13.92	.215	13.90	.214	13.83	.405
1.0 played minutes	20:09	6:44	17:49	6:20	13:48	6:09	20:56	10:45	16:28	5:38
1.5 played minutes	17:56	8:20	17:54	6:56	15:59	10:07	21:15	9:11	21:25	8:36
2.0 played minutes	15:59	9:43	19:35	8:03	18:37	10:44	17:50	9:22	16:45	8:50
2.5 played minutes	18:02	7:07	20:11	7:29	16:35	10:06	21:31	10:34	17:25	10:48
3.0 played minutes	21:32	8:36	23:08	7:34	21:35	11:12	20:38	10:05	19:04	8:53
3.5 played minutes	11:31	6:39	16:44	9:11	16:36	14:01	16:08	8:37	14:10	7:35
4.0 played minutes	15:30	7:33	17:38	7:45	13:53	8:54	17:58	8:43	19:17	8:17
4.5 played minutes	22:16	7:37	18:03	8:24	13:24	7:21	19:22	8:34	17:09	9:13

1.5 points (19:21), 1.0 points (18:08), 4.5 points (18:03), 2.0 points (17:45), 4.0 points (17:38), 2.5 points (16:49), and 3.5 points (15:05) in order. The difference in playing time between the medal group and the other group was in the order of 2.5 points ($p = .001$), 4.0 points ($p = .001$), 3.0 points ($p = .002$), and 1.5 points ($p = .025$). This shows that the difference in playing time was significant.

3.2.2 Composition and playing time by sports class between groups

Given the results in Table 6, the success rates of 2-point and 3-point shots showed a considerable difference except for the free throw success rate. The most significant difference was observed in the 3-point shot success rate ($p = .001$): that of the other group was 1.83 out of 8.01 attempts, while that of the medal group was 1.93 out of 6.49 attempts. This means that the success rate of the medal group (31.41%) was 9.69% higher than that of the other group (21.72%). As for the success rate of 2-point shots ($p = .001$), the other group was 23.46 out of 51.30 attempts, while that of the medal group was 28.07 out of 55.35 attempts. This means that the success rate of the medal group (50.73%) was 5.4% higher than that of the other group (45.33%). In contrast, the free throw success rate of the other group was 6.86 out of 12.17 attempts, while that of the medal group was 7.79 out of 12.95 attempts. Thus, the success rate of the medal group (57.64%) was 2.47% higher than that of the other group (55.17%), which means that the difference is statistically insignificant. The average offense rebounds, defense rebounds, steals, and block shots in each WB game were 8.22, 26.22, 19.61, 5.13, and 0.85, respectively. As these records were comparatively analyzed regarding game performance between the medal group and the other group, the difference in assist, defense rebound, and steal was significant. First, the number of assists ($p = .001$) in the medal group (22.94) was 4.47 more than that in the other group (18.47), which is a significant difference. The number of defense rebounds ($p = .008$) in the medal group (27.38) was 2 points more than that in the other group (25.38), which is a significant difference. The number of steals ($p = .016$) in the medal group (5.95) was 1.11 points higher than that in the other group (4.84), which is a significant difference. The number of turnovers ($p = .001$) in the medal group (9.40) was 3.82 points less than that of the other group (13.22), which is a significant difference. The number of fouls ($p = .001$) in the medal group (13.98) was 2.19 points less than that of the other group (16.17), which is a significant difference.

3.3 Trend analysis

The third set of research findings is about the trend in descriptive statistics of match records from 2012 to 2022 in Table 7. As to changes depending on the sports class, the quarterly sports class composition tended to decrease. As to the playing time, depending on the range of points, that of 1.0 points, 2.5 points, 3.0 points, and 4.5 points decreased, while that of 1.5 points, 2.0 points, 3.5 points, and 4.0 points increased. As to the playing time, depending on the range of points, that of 1.0 points, 2.5 points, 3.0 points, and 4.5 points decreased, while that of 1.5 points, 2.0 points, 3.5 points, and 4.0 points increased. Notably, the playing time of WB players of a mild case (4.5 points) decreased by about 5:07 min. In contrast, the number of players with 3.5 and 4.0 points increased by as much as 3:09 min and 3:47 min, respectively.

As time passed, one competition after another, the general scores and numbers of field shots, 2-point shots, free throws, rebounds, assists, block shots, and personal fouls decreased. In contrast, 3-point shot success rates and numbers of attempts, steals, and turnovers increased.

Mainly, 3-point shot successes and attempts increased as much as 0.74 and 3.64, respectively, in 2022 compared to 2012. The 2-point shot success rate also increased. Steals increased by as much as 1.75 and turnovers by 0.22 in 2022 compared to 2012.

4 Discussion

This study provides valuable insights for WB coaches to develop tactics and for players to enhance their performance by examining the latest trends in sports classification and performance that influence international WB at different performance levels. To achieve the objective of this study, official records and video games of 209 PG and WC were collected, and 418 match records in total were analyzed, including the ratings for each country. Furthermore, a non-parametric test, the Mann–Whitney *U*-test, was applied to examine differences in performance between groups. Additionally, trend analysis was conducted to identify players' progression in playing time by sports classes and performance over time. Firstly, match records of IWBF games from 2012 to 2022 were analyzed, and the results are as follows: Scoring factors directly affecting the game

TABLE 7 Game trend results from 2012 to 2022.

Year	2012		2016		2018		2020		2022	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
PTS	62.79	12.596	61.62	14.702	62.62	11.847	61.65	12.080	61.18	21.011
FGM	26.63	5.396	26.32	6.632	26.94	5.201	26.56	5.444	26.11	9.055
FGA	59.68	5.951	58.94	6.489	60.09	5.782	62.13	6.061	58.99	7.656
FG%	44.67	8.211	44.38	8.782	44.83	7.782	42.68	7.491	43.49	11.641
2PM	25.41	5.315	24.23	6.751	25.11	5.214	24.45	5.416	24.15	8.736
2PA	54.63	5.501	50.62	7.832	52.63	5.929	53.95	6.350	50.40	9.187
2P%	46.49	8.488	47.38	8.918	47.66	8.386	45.17	7.954	46.79	11.169
3PM	1.22	1.184	2.10	1.767	1.83	1.464	2.11	1.757	1.96	1.759
3PA	5.05	3.233	8.32	4.443	7.45	3.411	8.18	3.676	8.69	5.420
3P%	24.17	26.033	24.45	17.171	24.35	18.666	24.46	16.862	23.81	21.769
FTM	8.30	4.336	6.88	3.698	6.91	4.284	6.44	4.006	7.01	4.827
FTA	14.61	6.999	12.01	6.083	11.77	6.270	11.34	6.149	12.20	7.191
FT%	56.40	16.559	58.31	18.699	55.27	21.607	53.97	20.536	54.85	19.791
OR	8.74	3.616	7.94	3.316	8.71	3.707	8.18	3.775	7.68	4.062
DR	26.71	5.659	26.44	5.389	26.12	4.623	28.67	5.159	23.55	5.140
TOT	35.45	6.898	34.38	6.577	34.83	5.370	36.85	6.466	31.23	7.191
AST	19.36	5.174	20.58	6.334	19.30	5.298	21.44	5.200	17.64	7.034
STL	3.53	2.306	5.67	3.469	5.66	3.183	5.39	2.792	5.28	3.390
BLK	1.11	1.014	1.30	1.612	0.67	1.101	0.72	0.836	0.51	0.786
TO	11.54	4.374	13.56	5.613	12.84	5.290	11.54	4.606	11.76	6.422
PF	17.63	4.738	16.08	4.314	14.60	3.820	15.23	4.392	14.73	5.038

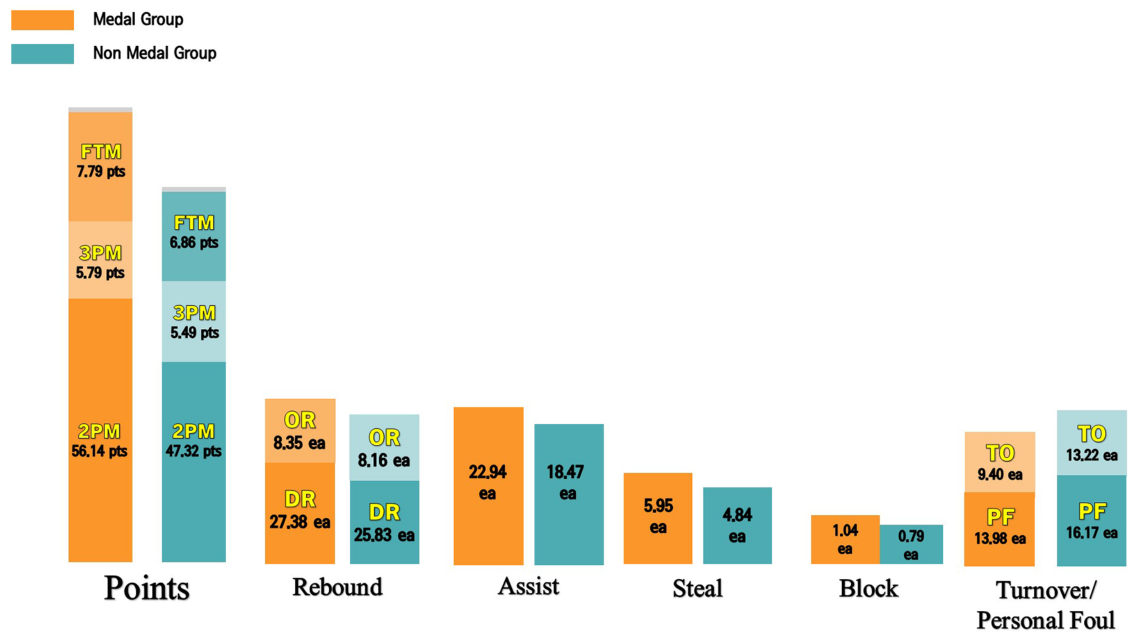

FIGURE 1
Game trend results from 2012 to 2022.

results were compared between the groups (see Figure 1). The result shows that the success rate of 2-point and 3-point shots was significantly different except for the free throw success rate, and the numbers of assists, defense rebounds, and steals were significantly different. This result shows that the medal group used various offensive tactics that contributed to scoring and hindered the other team from having opportunities for secondary scoring through defense rebounds and quick transitions. Prior research in basketball game analysis has shown that modern basketball prefers a fast-paced, aggressive style. That play is strongly associated with higher success rates in three-pointers, steals, and rebounds (21–23). As suggested by the results of this study, the international WB events show similar trends to those of basketball. Furthermore, the game performance showed differences in terms of defense rebound and steal, which contribute to switching the other team's scoring attempts into our team's offense opportunities, as well as assists that are directly related to scoring, just as in basketball games (12, 23–25). The difference in turnovers and fouls was also significant between the outstanding and the other groups. In addition, the medal group recorded fewer turnovers and fouls than the other group. According to the research, turnovers increase the probability of giving the other team opportunities to win a score, and it is known that turnovers increase the likelihood for the other team to win a score and cut off the flow of our team's offense on turnovers (26–28). If a particular player has many fouls and needs to prepare for free throw opportunities thoroughly, the player can be an easy target for the other team to score. The result of this study also shows that the medal group recorded smaller numbers of turnovers and fouls than the other group. Thus, compared to the non-medal group, the performers are making and attempting more shots that directly affect scoring (2-points, 3-points, and free throws), and they have a higher frequency of defensive rebounds and steals that contribute to taking control of the game. They also have fewer turnovers and mistakes, a sign of a team that plays a steady game and performs well.

Second, as for the difference between the groups depending on the sports class and game performance, the para-athlete's composition in each quarter depending on the sports class was as follows: the class of 13.92 points for 1 quarter, 13.91 points for 2 quarters, 13.88 points for 3 quarters, and 13.90 points for 4 quarters. As the medal group was compared with the other group, the average composition of the other group of para-athletes in quarters was higher than that of the medal group (1Q: 14 points, 2Q: 13.96 points, 3Q: 13.98 points, 4Q: 13.96 points) than the other group (1Q: 13.89 points, 2Q: 13.89 points, 3Q: 13.85 points, 4Q: 13.88 points), and the difference was significant. As to the difference between groups in sports performance, the difference in playing time between the medal group and the other group was in the order of 2.5 points ($p = .001$), 4.0 points ($p = .001$), 3.0 points ($p = .002$), and 1.5 points ($p = .025$). This shows that the difference in playing time was significant. In the medal group, the participation rate of players was even among different points. The class of 2.5 points participated in games about 4:30 min longer than the other group. The class of 2.5 points is considered significant since it can maintain the most stable posture among low classes of points and is highly capable of passing and shooting (29, 30).

Lastly, given the general trend in 2012 to 2022 international competitions, the sports class consideration in quarterly participation decreased. As to the playing time, depending on the

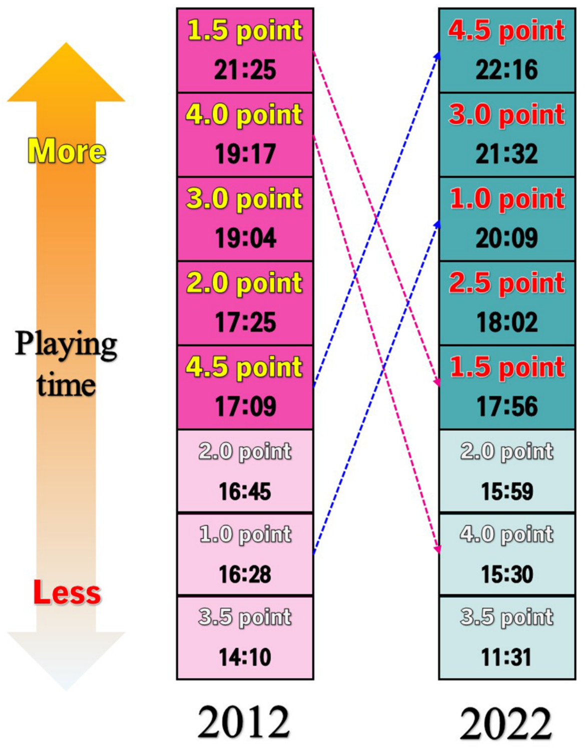

FIGURE 2
Comparison of playing time by sport class between 2012 and 2022.

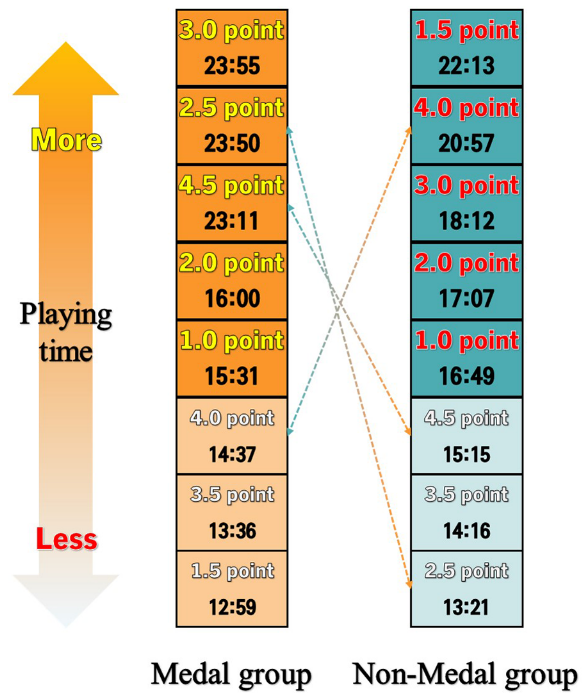

FIGURE 3
Comparison of playing time depending on the sport class in each group in 2022.

range of points, that of 1.0 points, 3.0 points, and 4.5 points decreased while that of 1.5 points, 2.0 points, 3.5 points, and 4.0 points increased. Notably, the playing time of WB players of a mild case (4.5 points) decreased by about 4:21 min. In contrast, the playing time of players with 3.5 and 4.0 points increased as much as 2:39 min and 3:47 min, respectively. Notably, the playing time of the classes of 4.5 points and 1.0 points significantly decreased (see Figure 2).

In WB, players of 4.5 points are of the mild case and play various roles in the team with relatively high motor abilities such as scoring and dribbling (29, 31). The playing time of players of 4.5 points decreased probably because the IWBF minimum disability criteria were revised in applying evidence-based sport classification as directed by the IPC after 2016 (31, 32). Among WB players attending the Tokyo PG held in 2021, sport classification was conducted again among players of 4.0 and 4.5 points. Except for 75% of the players who proved qualified among the 134, the rest had to undergo a reexamination. Some players with 4.5 points failed to meet the revised minimum disability criteria and thus could not attend the Tokyo PG (33). Further, players of 1.0 points have the most severe disability among WB players and, therefore, have limitations in wheelchair manipulation and moving speed. As WB advances, pursuing a fast pace has led to revisions. The roles of players of low points who had to play for less time were transferred to players of relatively high points, and the sports class of participant players was affected as a result (see Figure 3).

This study is significant because it examines the characteristics of WB games and analyzes trends in major game performance factors and sports class composition among major countries of excellent game performance, making visualized data available more efficiently and faster. It is expected that the findings of this study can be utilized effectively for game performance strategies that align with the most significant trend. In addition, this study will likely contribute to future studies on game performance in WB games. By analyzing the performance of WB and other para sports, this study aims to contribute to the growing field research supporting the development of these sports.

The limitations of this study are as follows. First, data were collected solely from official game records, and the analysis focused on objective factors centered around sport classification. Moreover, the scope of data collection was limited to the PG and WC, which restricted the range of available match data. Therefore, future studies should include position-specific analyses in addition to sport classifications, and explore key performance factors by incorporating data beyond official records—such as interviews with coaches involved in tactical decision-making. Furthermore, expanding the dataset to include recent tournaments and continental competitions would provide a more comprehensive understanding of performance in wheelchair basketball. In conclusion, we hope that future research will contribute to the development of effective strategies and efficient team compositions that reflect the unique characteristics of wheelchair basketball.

5 Conclusion

This study offers valuable insights for WB coaches to develop effective strategies and for players to enhance their performance by analyzing recent trends in sport classification and performance at the international level. The IPC continues to revise the classification system over specific periods to ensure fair competition and facilitate the participation of athletes with various types of impairments. As a result, countries are required to re-evaluate athlete classifications and select national representatives accordingly. This study confirmed that playing time varies across tournaments depending on the athletes' classifications, and this has a decisive impact on the selection of starting lineups. In high-performing countries, understanding the composition of classification points and their relation to playing time is a key factor in strategic planning.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

SL: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Writing – original draft, Writing – review & editing. M-CK: Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – review & editing.

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Analyzing coordinated group behavior through role-sharing: a pilot study in female 3-on-3 basketball with practical application

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A group often shares a common goal and accomplishes a task that is difficult to complete alone by distributing roles. In such coordination, the non-verbal behavior among three or more members complicates the explanation of the mechanism due to complex and dynamic interactions. In cognitive science, a crucial role is indicated: to intervene moderately with others and adjust the whole balance without interrupting their main smooth interactions, using an experimental task. The findings suggest that resilient helping actions in the third role support coordination. These actions are similar to off-ball movements in team sports, which involve an on-ball player and have recently been the focus of sports science because their characteristics are not represented in common statistical data, such as a shooting success rate. Hence, a new perspective for discussing coordination has emerged, as existing theories, such as synchronization—where movements between players are spontaneously matched and organized—cannot explain the mentioned role. However, there is a lack of investigation and discussion regarding whether these findings are applicable to real-world activities. Therefore, this study applied the experimental findings to the field of sports. We developed a 3-on-3 basketball game in which the offensive role of intervention decision and adjustment is key for winning and introduced it to the practice of a female university team as a pilot study. Participants repeatedly engaged in the mini-game, and the playing was compared before and after receiving tips for this role. Consequently, in the bins of the relatively large distance between the participant required to the relevant role and each defensive player, the frequencies after receiving these tips were significantly higher. Furthermore, the winning rate on the offensive team improved temporarily; however, the effects were not maintained. These suggest that spacing skill, which maintains reasonable distances from the other players, creates favorable situations for coordination. This study may bridge the gap between controlled experiments and real-world applications and make an educational contribution; it may recommend practice design for the acquisition of spacing skills related to the crucial role.

KEYWORDS
coordination, group behavior, role-sharing, adjustment, sports

1 Introduction

A group often shares a common goal and accomplishes a task that is difficult to complete alone by distributing roles among its members. This is explained by common opinions or suggested through experiments and simulations in many previous studies [e.g., (1–4)]. This idea is encapsulated by the saying "Two heads are better than one" and is defined as planned coordination (coordination) in psychology and cognitive science (5). For coordination, members share some roles considering the workloads and task specifications. Distributed cognition theory explains that an overall group function works through interactions among subsystems and between subsystems and environments, in which each subsystem plays a role (6, 7). The internal and external resources are properly distributed, and each member's workload decreases. Furthermore, cognitive interactions among roles based on different perspectives lead to problem-solving and the discovery of various strategies [e.g., (8–12)]. Team sports, in particular, are typical examples of the benefits of role-sharing by multiple on- and off-ball players [e.g., (13–16)]. This is required to achieve a common goal and high performance under rules, time constraints, and defensive pressures. Team sports often involve three or more members and aim to achieve a common goal through complex and dynamic interactions. Complexity indicates that explaining the coordination mechanism is more complicated than for a pair because relationships among members diversify, such as role-sharing, and are not interpreted by one-dimensional behaviors such as leader-follower and approach-avoidance (17, 18). Dynamics suggests non-verbal and time-series features that develop strongly over a short period, such as body movements (19, 20). Cognitive science focuses mainly on higher-order information processing, and coordinated behaviors among three or more members are not fully investigated. Considering that physical interactions are primitive and that a group of three or more members is often observed in real-world activities, it is important for cognitive science, which discusses social intelligence, to investigate complex and dynamic coordination (17).

This study focuses on a crucial role in the coordinated behavior of a triad through role-sharing, which is indicated using an experimental task in a cognitive science study (21). We aim to bridge a gap between experimental findings and real-world applications and contribute to the understanding and development of coordination mechanisms.

In related works, a sports science study recorded 5-on-5 basketball games and identified the coordinated defensive structures of role-sharing according to emergent situations by a top-level male university team in Japan (1). Recently, machine learning studies have predicted shooting success rates and evaluated coordination leading to goals by classifying and extracting features of physical interaction structures with role-sharing using datasets in basketball and soccer [e.g., (22–24)]. Furthermore, network science studies have identified indices of centrality in network models where nodes and links are regarded as players and pass in soccer, representing team-specific strategies and key players related to robust coordination [e.g., (25–27)]. Meanwhile, collective behavior studies observed coordinated hunting and found that the role-sharing of chasing and blocking naturally emerged [e.g., (28, 29)]. Additionally, multi-agent simulation using deep reinforcement learning can replicate this process. In the simulation, agents perceive and observe the environment, including the prey, and learn the optimal behaviors to maximize their rewards (30). The findings in sports science, machine learning, network science, and collective behavior suggest that role-sharing creates favorable situations for coordination. In principle, these studies aim to understand the physical interaction structures in coordination. However, the information processing underlying these characteristics has not been fully discussed, and educational applications have not been considered.

Notably, although not competitive, a previous cognitive science study investigated a crucial role in the coordinated behavior of a triad through role-sharing using an experimental task (21). This indicates that the role of intervening moderately with other roles and adjusting the whole balance was related to high task performance. Such resilient helping actions are an important factor for successful defensive coordination in team sports and effective team building in business and military organizations, not only in experimental tasks [e.g., (1, 31–34)]. This role is also required not to interrupt their main smooth interactions. The third role needed to decide whether to intervene according to the situation. A new perspective for discussing coordination has emerged because existing theories in cognitive science and sports science, such as synchronization [e.g., (35–38)]—where movements between players are spontaneously matched and organized—cannot explain this role. The findings suggest that adjustment to create favorable situations without interrupting others supports coordination. This concept is similar to off-ball movements in team sports involving an on-ball player. For example, in basketball, when an on-ball player is surrounded by defensive opponents, another offensive player approaches and directly receives a pass for helping. Off-ball movements in basketball and soccer have recently been the focus of sports science, as shown by distances between players and those with the goal. These contain valuable information on coordination and are not represented in common statistical data, such as shooting success rate [e.g., (13, 16, 39, 40)]. The previous study (21) confirmed the crucial role in coordination; however, there is a lack of investigation and discussion regarding whether these findings are applicable to real-world activities.

Therefore, we applied the experimental findings to the field of sports as a pilot study. This study focused on team sports that must achieve a common goal and high performance within some constraints. We used 3-on-3 basketball in which the coordination by off-ball players is essential for winning, as mentioned above. Furthermore, it is easy to record group behavior because of the relatively small number of players (three on each team) and the court size. Additionally, it has recently attracted worldwide attention, as evidenced by its inclusion as an official Olympic event. Meanwhile, few studies have used 3-on-3 basketball to discuss coordination in terms of cognitive science. The purpose of our study was to investigate the influence of the role of intervention decision and adjustment on coordination in 3-on-3 basketball. We developed a mini-game in which the relevant offensive role is key and introduced it to the practice of a female university team. The players repeatedly engaged in the game. After the first half, the offensive team received tips on coordination focusing on this role. The team performance and playing related to the relevant role were quantitatively compared before and after receiving these tips. According to the purpose, this study has set the following hypothesis: after receiving the tips, the team performance improves, and the appropriate role executions are observed.

Our study connects cognitive science and sports science because this pilot study includes an investigation of information processing underlying complex and dynamic coordination, which has not yet been fully discussed. The quantitative analysis may recommend practice design on playing that helps an on-ball player and creates favorable situations in the fields of sports. Bridging the gap between controlled experiments and real-world applications is a challenging endeavor. These findings may also offer implications for further developing 3-on-3 basketball itself. Next, we explain the details of this practice.

2 Methods

2.1 Participants

Six female students on the university basketball team, of which the second author is the head coach, participated in this practice. They usually play 5-on-5 in the official game. This team was affiliated with the third division of the Tokai area league in Japan, practiced regularly for about 2 h each time three or four times a week, and played approximately 30 games per year including practice matches. The participants included five regular players and a sixth man. The sixth man means a first substitute player. Their averages of age, height, and basketball experience were 19.17 age (SD = 0.90), 165.08 cm (SD = 5.88), and 10.58 years (SD = 2.70), respectively.

The participants were divided into the offensive and defensive teams. The head coach conducted the team compositions to make their abilities competitive based on their profile data of age, dominant hand, height, basketball experience, and current and previous positions (see the details on the offensive and defensive teams in Supplementary Materials). The second author has 25 years of coaching experience and holds a certified B-level coaching license from the Japan Basketball Association. The record includes leading a university team to promotion to the first division of the Tokai area league and participation in national tournaments in Japan. The participants on each team were fixed. This study statistically compared the offensive team performance and playing related to the role of intervention decision and adjustment before and after receiving the tips of this role. Hence, we planned this practice based on the policy of eliminating factors other than these tips as much as possible. Meanwhile, it should be kept in mind that we applied the experimental findings to the field of sports as a pilot study.

2.2 Informed consent

We explained how we would video-record and collect data. When explaining, not all the participants were informed of the details of the procedures in this practice. They were not made aware of the playing related to the role of intervention decision and adjustment, receiving the tips of this role to the offensive team, and comparing the offensive team performance and playing before and after receiving these tips. The procedures were also based on the policy of eliminating factors other than the tips. Written informed consent was obtained from all the participants. This study was approved by the ethics and safety committee of Shizuoka University and Tokoha University, to which the first author and the participants were affiliated. Our study was conducted following these regulations. According to the informed consent, not all images in the manuscript contain individual identifiers.

2.3 Developed 3-on-3 basketball game

Figure 1 shows the diagram of the developed mini-game in which the circles and squares represent the offensive and defensive players, respectively. Players from #1 to #3 on each team are the same participants in all the games (trials). Offensive #3 is required to play the role of intervention decision and adjustment focused on in this study. The winning condition for the offensive team is that within a 15 s time limit, someone draws a defensive player and a shooter is unmarked in open space. Conventionally, the defensive team must play without satisfying it. To investigate coordination, the above condition is defined independently of individual skills. The team performance reported in the Results section is consistent with this definition.

In the mini-game, we set some rules to guide the same situation at the start of the game and compare the playing before and after giving the tips about the role of intervention decision and adjustment. The ball handler #1 is fixed, and the player begins the game without directly passing to #3. The starting position of each offensive player is assigned to maintain a certain distance to observe the coordination process in which this role involves the other players. On the defensive team, #1 and #2 confront offensive #1 and #2 and their starting positions are voluntary. The start position of defensive #3 is also voluntary. Just before the game, the two-man game is randomized on the right (Figure 1) or left side of the basket goal by instructions to eliminate the influence of the dominant hand. The starting positions on the offensive team are called the two-guard and also used in a 5-on-5 game. For the offensive team to win, it is important that #3 intervenes with the other players, adjusts the two-man game, and creates favorable situations, such as (1) handing the ball off directly with #1 or #2 ("hand-off"), (2) working as a wall to interrupt the defensive player ("pick and roll"), and (3) moving to a corner area and taking a three-point shot. Conversely, it is also key not to

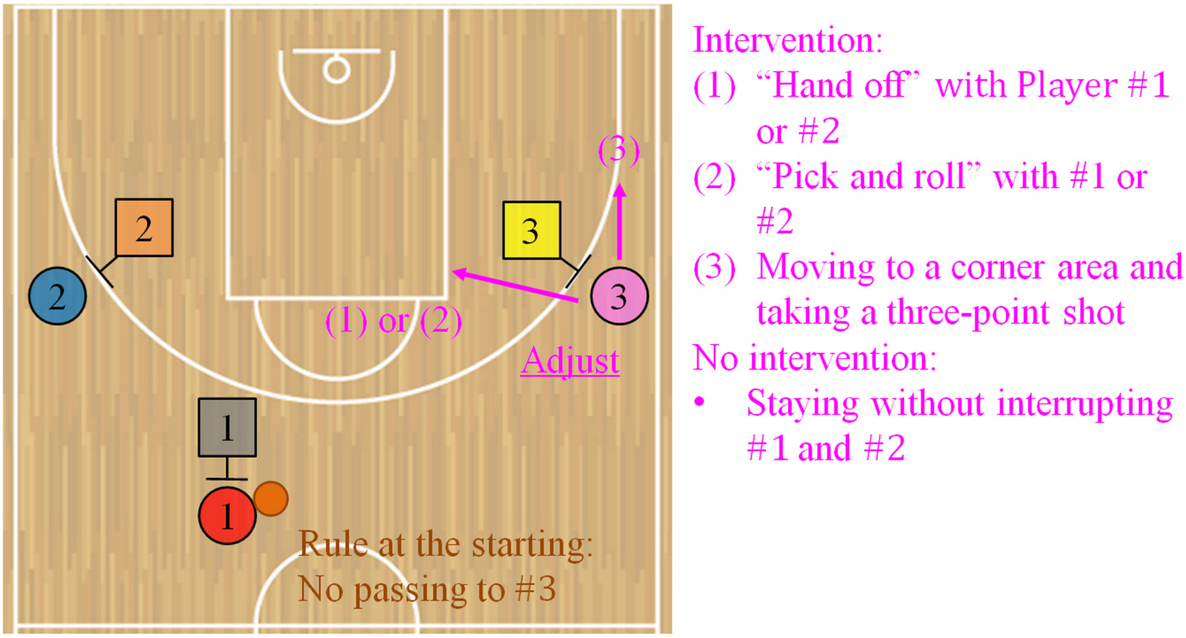

FIGURE 1
Diagram of the developed 3-on-3 basketball game in this study. In this mini-game, the circles and squares represent the offensive and defensive players, respectively. The winning condition for the offensive team is that within a 15 s time limit, someone draws a defensive player and a shooter is unmarked in open space. At the start of the game, the ball handler of #1 is fixed, and the player begins without directly passing to #3. The starting position of each offensive player is assigned (see the Developed 3-on-3 basketball game section to confirm the other rules). For the offensive team to win, #3 is a key player; it is required to intervene with the other players, adjust the two-man game, and create favorable situations, such as (1) handing the ball off directly with #1 or #2 ("hand-off"), (2) working as a wall to interrupt the defensive player ("pick and roll"), and (3) moving to a corner area and taking a three-point shot. Conversely, it is crucial not to interrupt #1 and #2 without forcibly intervening according to the situation.

interrupt #1 and #2 without forcibly intervening according to the situation. The offensive coordination required in this game is fundamental. However, the head coach mentioned that the participants could not implement such interaction in official games at that time.

2.4 Environment and procedures

The upper part of Figure 2 shows the environment of the mini-game conducted in the university gymnasium. The court area, including the vertical endline and the area under the basket goal ("paint area"), followed the official size of 3-on-3 and 5-on-5 (41, 42), except for the horizontal sideline. A digital countdown timer was used to watch the remaining time (Mollten Corp., UX0110). The participants regularly practiced on this court size in the gymnasium. Hence, factors such as the court area, lighting, and flooring were unlikely to negatively influence the offensive team's performance and group behavior. The mini-games were recorded from a bird's-eye view on the stage using only one video camera, as shown in the lower part of Figure 2 (Sony Corp., HDR-CX680). As they played all the trials within the camera's field of view, there were no issues with tracking their positions by image processing technology as below. We preliminarily prepared another video camera; however, no equipment problems occurred during this practice. Consequently, these recordings were excluded from this analysis.

Regarding the procedures, the experimenter briefly announced the practice schedule (see these details in Supplementary Materials). Subsequently, the participants warmed up and received colored bibs for individual identification (Figure 1). The experimenter then explained the team assignments and mini-game rules. At this point, the first author did not instruct the offensive team on the role of intervention decision and adjustment and playing. The three practice trials, including a trial by the timer error, were conducted and they could confirm the rules. Subsequently, in the first half of the pretest, three sessions comprising seven trials per session were conducted for a total of 21 trials. The interval between the trials was approximately 30 s, with approximately a minute between the sessions. The university team regularly played a 5-on-5 game with each quarter for 10 min with the 2 min intervals for a total of 40 min across the four quarters. In comparison, the total of playtime in this practice was a maximum of approximately 10 min. Hence, fatigue was unlikely to negatively influence the offensive team performance and group behavior. Furthermore, we carefully checked the participants just before restarting the mini-game to ensure no fatigue. After the first half, a guest coach who understood the purpose of this study gave each team tips

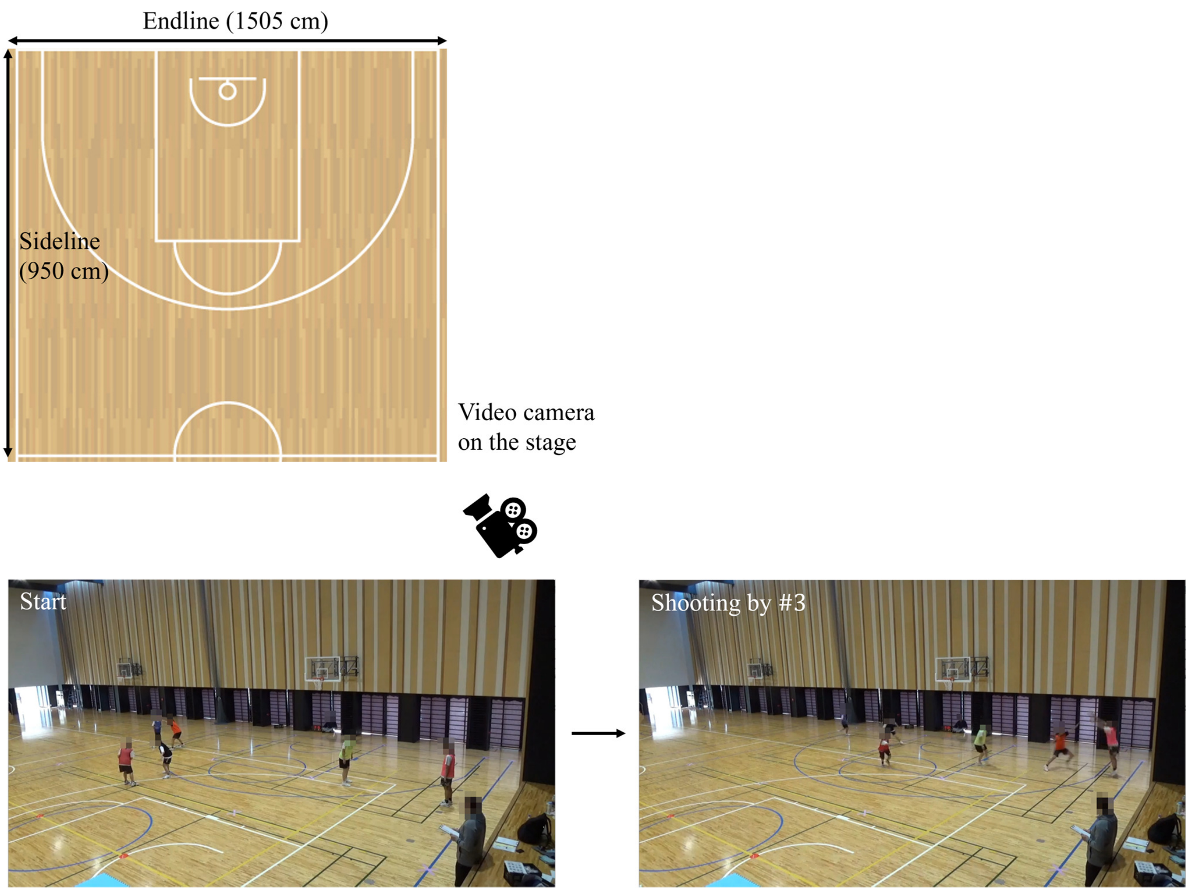

FIGURE 2
Environment in this practice. We conducted the developed 3-on-3 basketball game in the university gymnasium. The court area, including the vertical endline and the area under the basket goal ("paint area"), follows the official size in 3-on-3 and 5-on-5 (41, 42), except for the horizontal sideline. All the images in the mini-games were recorded from a bird's-eye view on the stage using only one video camera by the first author. After receiving the tips about the role of intervention decision and adjustment, #3 required for this role, wearing a pink bib as shown in Figure 1, moves to a corner area while maintaining a reasonable distance from each defensive player and aims to take a three-point shot, as shown in the lower images. We explained how we would video-record and collect data. Written informed consent was obtained from all the participants. According to the informed consent, all the images are shown while blurring some parts to avoid identifying individuals.

based on the observations of the games. The coach was a professional player in Japan and is currently the head coach of a junior youth team. In this practice, giving tips that reflected the essence of our study to the offensive team was indispensable. Thus, we asked the guest who is superior to coaching to do so. The tips for the offensive team focused on coordination related to the role of intervention decision and adjustment. Meanwhile, the defensive team received the general tips on help defense, excluding participant- and game-specific strategies. Table 1 presents the details of the tips given to each team. While one team received them, another waited at a distance to prevent information gathering. Generally, it is common for a team to keep strategies hidden from the opponent. The purpose of this study was to investigate the influence of the tips on the offensive team performance and playing related to this role. Hence, we planned this practice based on the policy of eliminating factors other than giving offensive tips; the mentioned procedure was appropriate. Subsequently, the second half of the posttest was conducted similar to the first one.

3 Results

3.1 Team performance

This study counted the winning numbers of the mini-games for the offensive team to compare them between the first and second halves. Those indicated in the first half for a total of 21 trials from Sessions 1 to 3 and in the second one from Sessions 4 to 6 were 9 and 11, respectively. Table 2 represents a cross-tabulation table of the event and performance. A chi-square test indicated no significant relationship between them, and the effect size ϕ was small ($\chi^2(1) = 0.095$, $p = 0.757$, $\varphi = 0.048$). Meanwhile, Figure 3 shows the progression of the winning rates on the offensive team over the sessions. The rates of Sessions 1 and 2 in the first half were at the chance level, indicating four wins in the seven trials; thereafter, it decreased in Session 3. Notably, in the second half, it recovered in Session 4 and drastically improved in Session 5, indicating six wins; however, it significantly decreased in Session 6. It indicated that after receiving the tips about the

TABLE 1 Tips to the offensive and defensive teams by the guest coach.

Team	Tips
Offense	• #3 checks the position of defensive #3. When defensive #3 helps, #3 moves to where the driving offensive player (#1 or #2) can see #3, such as a corner area ("deep corner") so that #3 can easily take a three-point shot in open space • The very first thing #1 and #2 should do is to play a two-man game where #1 or #2 drives, that is, dribbles toward the area under the basket goal ("paint area"). If #1 pretends to cooperate with #2 working as a wall to interrupt the defensive player ("pick and roll") and drives to the other side of the wall ("reject"), defensive #3 has to move to help. Then, #3 moves to the corner along the three-point line taking advantage of a wide space • However, as an exception, in a case where #3 is in a high position (two-man game position), if defensive #3's back is visible from #3 and defensive #3 goes for help, #3 should dive to the paint area because moving along the three-point line and receiving the pass takes time • #3 should not move too much. #3 should carefully check the defensive players' positions while staying around: (1) the wing position (45° position on the three-point line with the goal as the origin), (2) the position near the three-point line changing from straight to curved, or (3) the corner position.
Defense	• If #3 does not help, the space near the goal becomes open for a shot, so #3 has to move to help. If offensive #3 receives the ball, #3 should mark offensive #3 immediately. The defensive players need to check where the ball is and it makes it easier to help. If not, the offensive player can take an uncontested shot with a running jump ("lay-up shot") • Force the offensive player to make a long, arching pass to buy time for getting the defensive ones ready. The defensive players' keeping their hands up will force the offensive one to make an arching pass, creating time for them to close the distance with the offensive one ("closeout").

The # indicates each participant in each team in Figure 1. Offensive #3 is required for the role of intervention decision and adjustment focused on in this study. Single and double underlines correspond to the intervention and non-intervention with the other players, respectively. Double quotation marks represent technical terms in basketball.

TABLE 2 Cross-tabulation table of the event and offensive team performance.

Event	Offensive team performance	
	Win	Loss
First	9	12
Second	11	10

role of intervention decision and adjustment, the offensive team performance improved temporarily but was not maintained.

In summary, giving the tips about the role of intervention decision and adjustment did not fully influence the offensive team's performance. The main reason for the decrease in the winning rate in the final session was that the defensive team had established an effective countermeasure, as reported by the participants on the defensive team (see these details in the Discussion section). The offensive team might not achieve developed coordination based on the tips of this role because of some factors such as only a single practice and individual skills.

3.2 Analysis procedures of playing related to the offensive role of intervention decision and adjustment

We obtained time-series position data of each participant in the two dimensions, x- and y-components, through the image processing of a bird's-eye view recording (Figure 2). This study compared the movements of offensive #3, required for the role of intervention decision and adjustment, as shown in pink in Figure 1, between the first and second halves using the dataset. The participants in the movies (20 fps, 1,280 px × 720 px) were tracked using ByteTrack (43) based on YOLOX. The experimenter manually corrected false detections and undetected positives using the labeling platform Labelbox (44) and prepared the dataset from real coordinate transformations. The average of the absolute measurement errors was 3.165 cm × 2.102 cm, similar to those (2.3 cm × 4.6 cm) reported in the previous study (18) that investigated passing coordination by a triad in soccer. Considering the bin interval of 200 cm in the histogram used in the analysis explained below, the errors in our study were unlikely to negatively influence the results. Meanwhile, in this practice, it is difficult to detect a ball using image processing technology due to the recording environment and technical problems; this is future work.

This study analyzed (1) the distance (cm) between the offensive participant required for the role of intervention decision and adjustment and each defensive player, as shown in black, orange, or yellow in Figure 1, and (2) the distance between the offensive key player and each other participant, as shown in red or blue in Figure 1. We evaluated spacing skill to play this role. Spacing skill, which maintains reasonable distances from other players, is generally crucial for both offensive and defensive coordination in basketball [e.g., (13, 14, 16, 45, 46)]. In the mini-game, if reasonable distances from the defensive players are maintained, the defensive pressure is reduced, which makes it easy to intervene moderately with the other offensive players according to the situations, as explained in Table 1. If those among the offensive players are maintained, it is easy to pass the ball to the relevant role, and the defense will break down. The characteristic is also represented by staying in place without interrupting the other offensive players, as shown in Table 1. This analysis calculated both indices of (1) and (2) for each time frame and made these histograms. Histogram analysis is a fundamental method to understand overall trends for investigating complex and dynamic coordination. It has been used in previous studies on group behavior [e.g., (4, 47, 48)] because of its advantage in intuitively capturing the characteristics of continuous values. Histograms were generated in each trial, and the normalized frequencies were averaged for the first and second halves. A t-test was conducted to compare them between the first and second halves in each bin. It is expected that significant differences in the frequencies for the indices of (1) and (2) are confirmed because of giving the tips of this role. This study conducted exploratory comparisons of reasonable distances between the participants because of analyzing complex and dynamic group behavior in the field of sports.

The previous studies (4, 48) conducted the t-test in each bin of a histogram to statistically compare frequencies between different

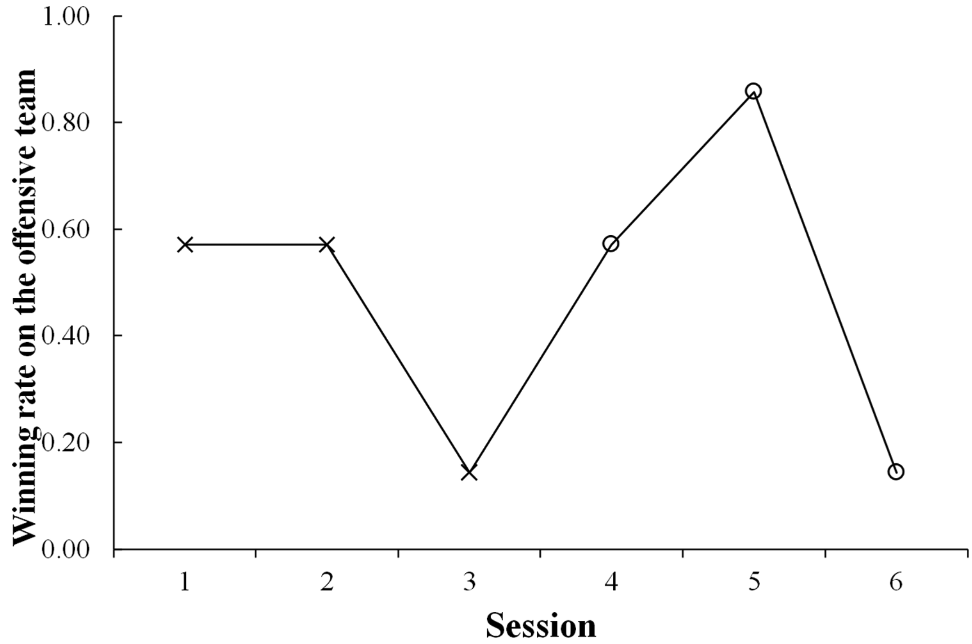

FIGURE 3
Progression of the winning rates on the offensive team over the sessions. Each session consists of seven trials. After Session 4, given the tips about the role of intervention decision and adjustment, the team performance improves temporarily but is not maintained.

conditions. However, we should keep in mind the type I error by the multiple comparisons. Therefore, this study calculated the effect sizes (Cohen's d) and powers (1-β) in all the bins for both indices of (1) and (2) to improve the validity of the statistical tests and carefully interpret these results. For calculating the powers, we set the significant level at 5% ($\alpha = 0.05$), effect sizes, and sample size n (21 trials) in each half. We comprehensively evaluated the differences between the first and second halves in terms of the p-value, effect size, and power indices. The Bonferroni method was not applied to avoid this because the numbers of the bins in both indices of (1) and (2) were large and it was easy to cause the type II error. Our policy was to avoid this problem by calculating the three indices and investigating the significant differences between the first and second halves from different perspectives. The distances between the participants were analyzed using MATLAB R2021b. The statistical tests and the investigation of these validities were conducted using R 4.3.3 and G*Power 3.1, respectively. However, it is crucial to compare the playing related to the role of intervention decision and adjustment using applied statistical methods before and after giving the tips of this role; this is also future work.

3.3 Results of the distance with each defensive player

Figure 4 shows a time-series example of the distance (cm) between the offensive participant for the role of intervention decision and adjustment and each defensive player in a trial. Figure 4 also shows the histogram in each session. The upper and lower parts represent those in the first and second halves, respectively. The horizontal and vertical axes indicate the bin and average of the normalized frequencies across the seven trials of each session, respectively.

In each bin, the average of normalized frequencies across the 21 trials in the first half from Sessions 1 to 3 was compared with that in the second one from Sessions 4 to 6. Notably, the t-tests confirmed the significant differences in the bins of 400 cm, 1,200 cm, and 1,400 cm, and these effect sizes ranged from medium to large while the powers were high [400 cm: $t(20) = 2.739$, $p = 0.013$, $d = 0.894$, 1-$\beta = 0.973$; 1,200 cm: $t(20) = -2.269$, $p = 0.034$, $d = 0.732$, 1-$\beta = 0.891$; 1,400 cm: $t(20) = -2.581$, $p = 0.018$, $d = 0.668$, 1-$\beta = 0.829$; Figures 5A–C). In the bin of a relatively small distance of 400 cm, the frequency in the second half was significantly lower than that in the first one. Conversely, in the bins of relatively large distances of 1,200 cm and 1,400 cm, the frequencies in the second half were significantly higher than those in the first one. In the other bins, no significant differences were confirmed (see these details in Supplementary Materials).

3.4 Results of the distance with each other offensive player

Figure 6 shows a time-series example of the distance (cm) between the offensive player required for the role of intervention decision and adjustment and each other participant in a trial. Figure 6 also shows the histogram in each session. The upper

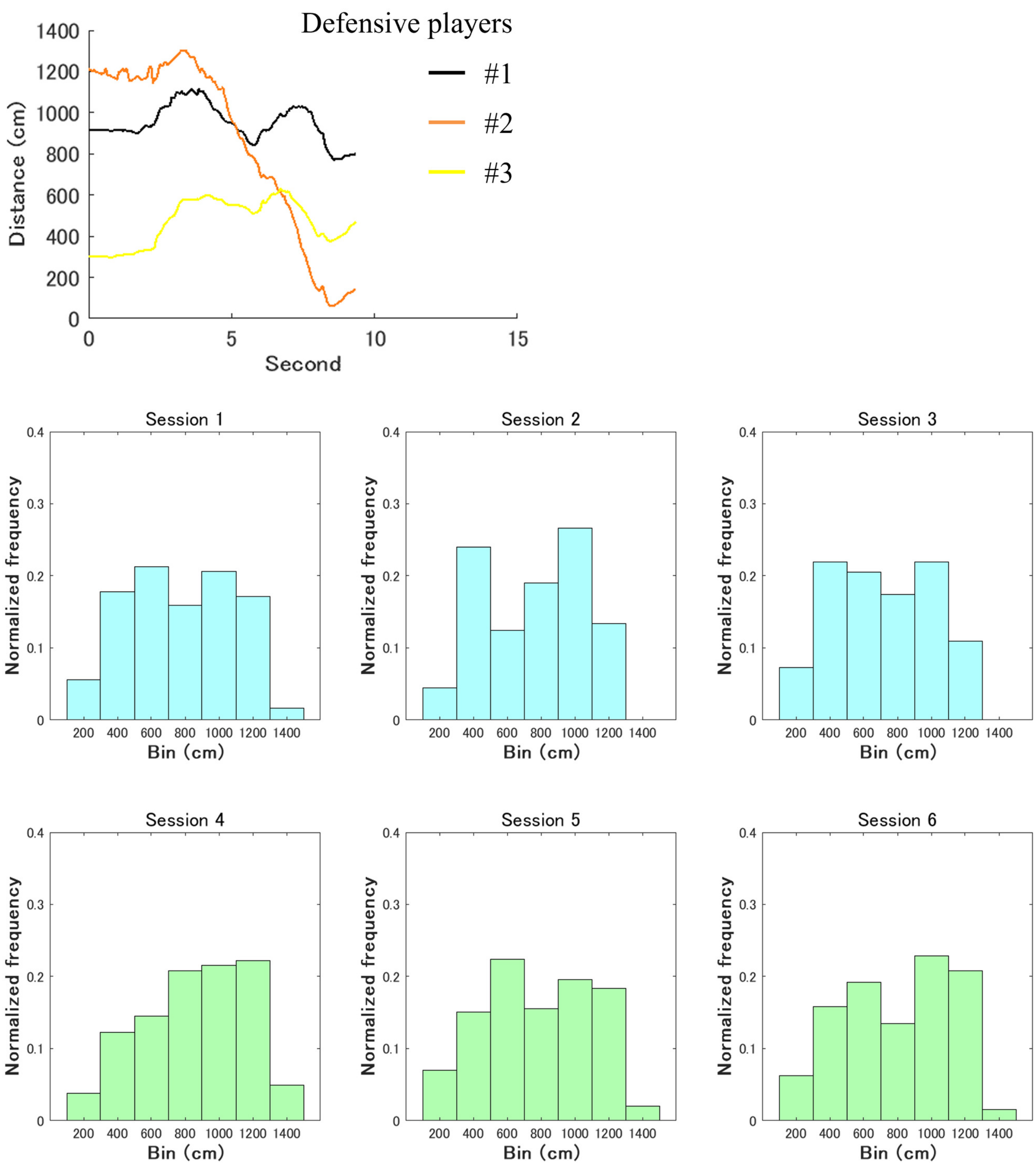

FIGURE 4
Overall characteristics of the distances (cm) between the offensive player required for the role of intervention decision and adjustment and each defensive participant. Its time-series example in a trial fluctuates up and down. Meanwhile, the upper and lower parts represent the histograms in the first and second halves, respectively. The horizontal and vertical axes indicate the bin and average of the normalized frequencies across the seven trials of each session, respectively.

and lower parts represent those in the first and second halves, respectively. The horizontal and vertical axes indicate the bin and average of the normalized frequencies across the seven trials of each session, respectively.

In each bin, the average of normalized frequencies across the 21 trials in the first half from Sessions 1 to 3 was compared with that in the second one from Sessions 4 to 6. Considering the results of the *t*-tests, effect sizes, and powers, the clear differences were not confirmed between the first and second halves. Although the effect sizes were medium and the powers were lower than those reported in the previous section, the *t*-tests indicated the significant trends of differences in the bins of 200 cm, 800 cm, and 1,600 cm [200 cm: t (20) = −2.002, $p = 0.059$, $d = 0.517$, $1\text{-}\beta = 0.616$; 800 cm: t (20) = 1.856, $p = 0.078$, $d = 0.628$, $1\text{-}\beta = 0.782$; 1,600 cm: t (20) = −1.745, $p = 0.096$, $d = 0.572$, $1\text{-}\beta = 0.703$; Figures 7A–C). These showed a U-shape trend; in

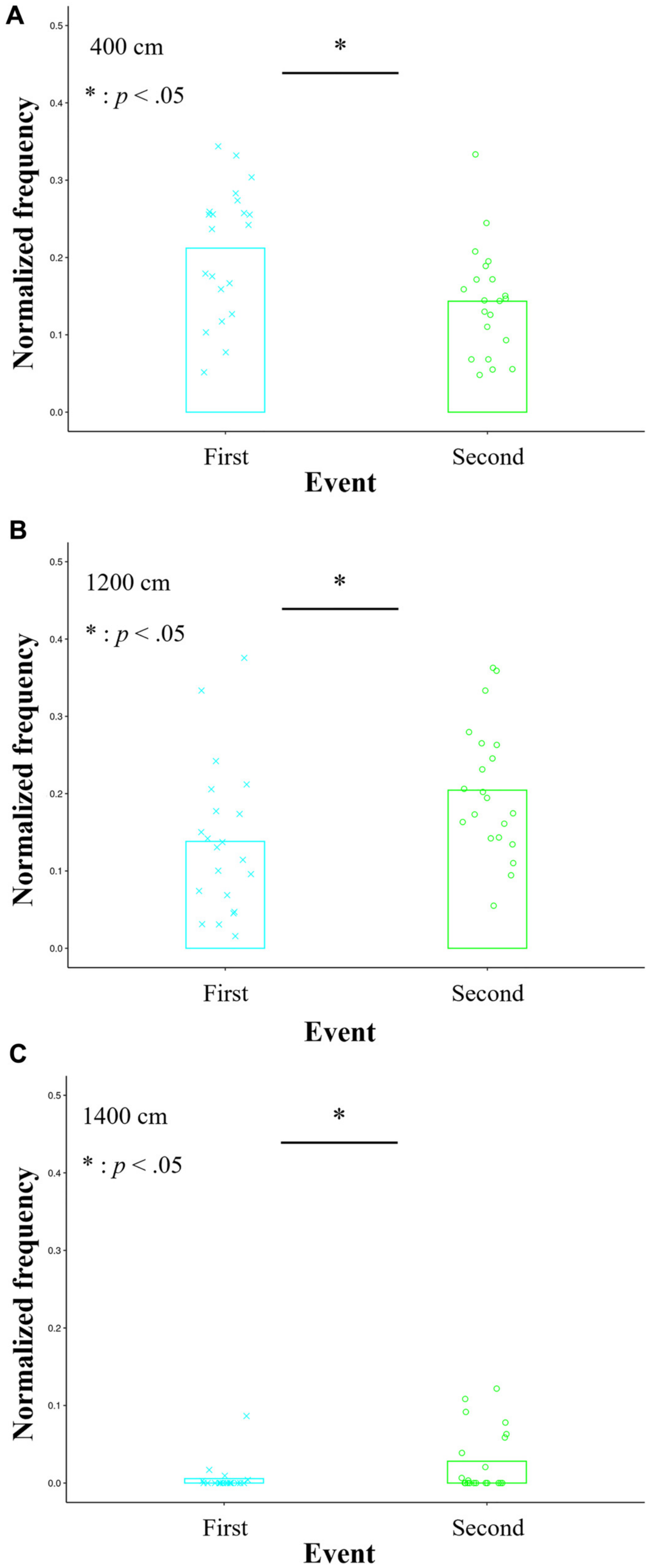

FIGURE 5
Averages of the normalized frequencies in the bins confirmed the significant differences between the first and second halves in the histograms of Figure 4. In the bin of a relatively small distance of 400 cm (A), the normalized frequency in the second half is significantly lower than that in the first one. Conversely, in the bins of relatively large distances of 1,200 cm (B) and 1,400 cm (C), the frequencies in the second half are significantly higher than those in the first one.

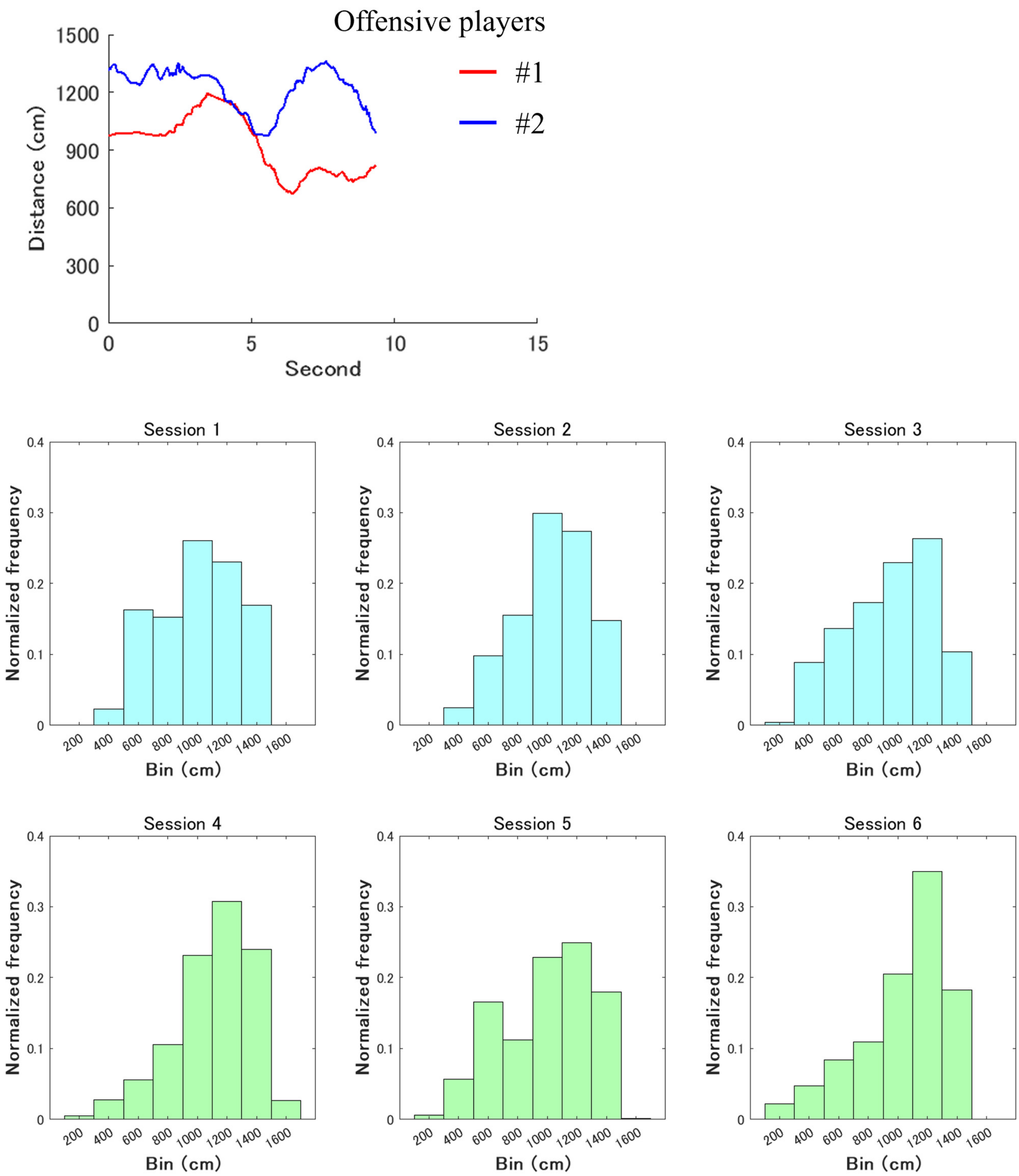

FIGURE 6
Overall characteristics of the distances (cm) between the offensive player required for the role of intervention decision and adjustment and each other participant. Its time-series example in a trial fluctuates up and down. Meanwhile, the upper and lower parts represent the histograms in the first and second halves, respectively. The horizontal and vertical axes indicate the bin and average of the normalized frequencies across the seven trials of each session, respectively.

the bins of relatively small and large distances of 200 cm and 1,600 cm, respectively, the frequencies in the second half tended to be significantly higher than those in the first one. Conversely, in the middle bin of 800 cm, the frequency in the second half tended to be significantly lower than the first one. In the other bins, no significant differences were confirmed (see these details in Supplementary Materials).

4 Discussion

This study developed the mini-game of 3-on-3 basketball, in which the offensive role of intervention decision and adjustment is crucial for winning. We introduced it to the practice of the female university team as a pilot study. The purpose of our study was to investigate the influence of this role

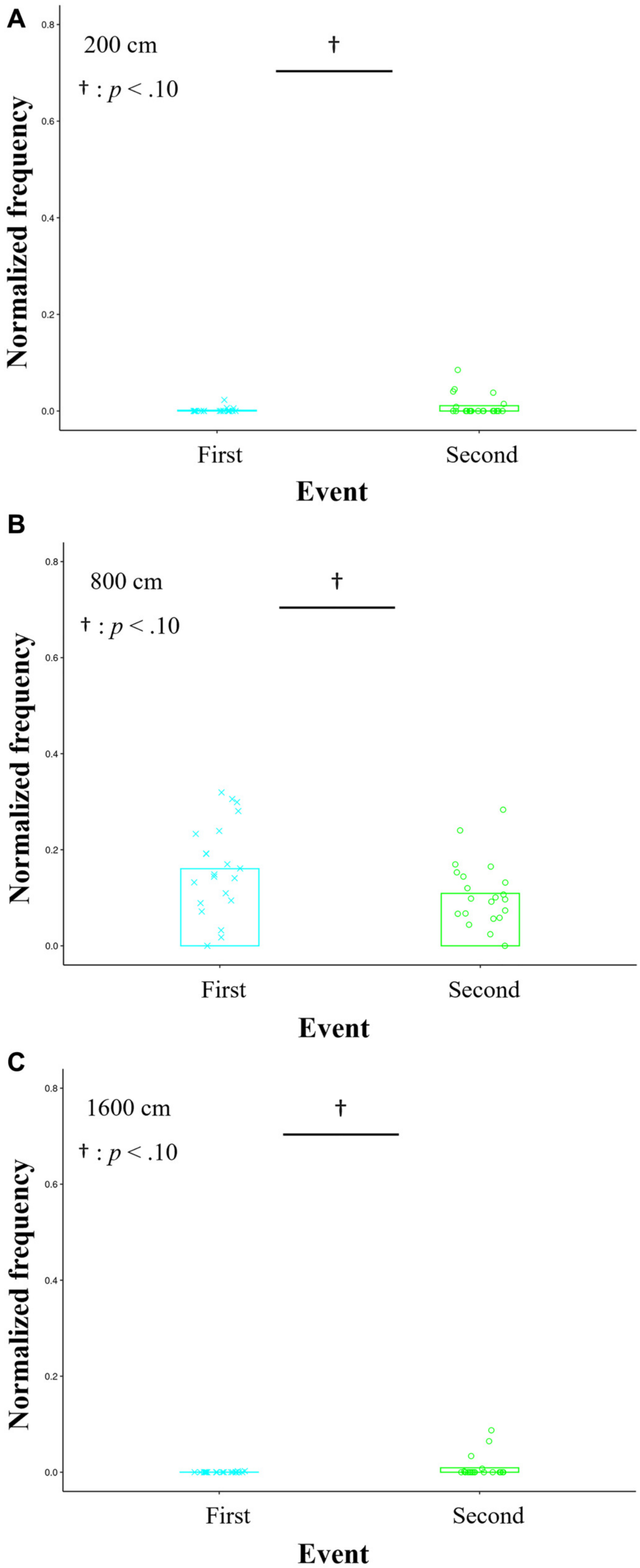

FIGURE 7
Averages of the normalized frequencies in the bins confirmed the significant trends of differences between the first and second halves in the histograms of Figure 6. In the bins of relatively small and large distances of 200 cm **(A)** and 1,600 cm **(C)**, respectively, the normalized frequencies in the second half tend to be significantly higher than those in the first one. Conversely, the frequency in the middle bin of 800 cm **(B)** in the second half tends to be significantly lower than that in the first one.

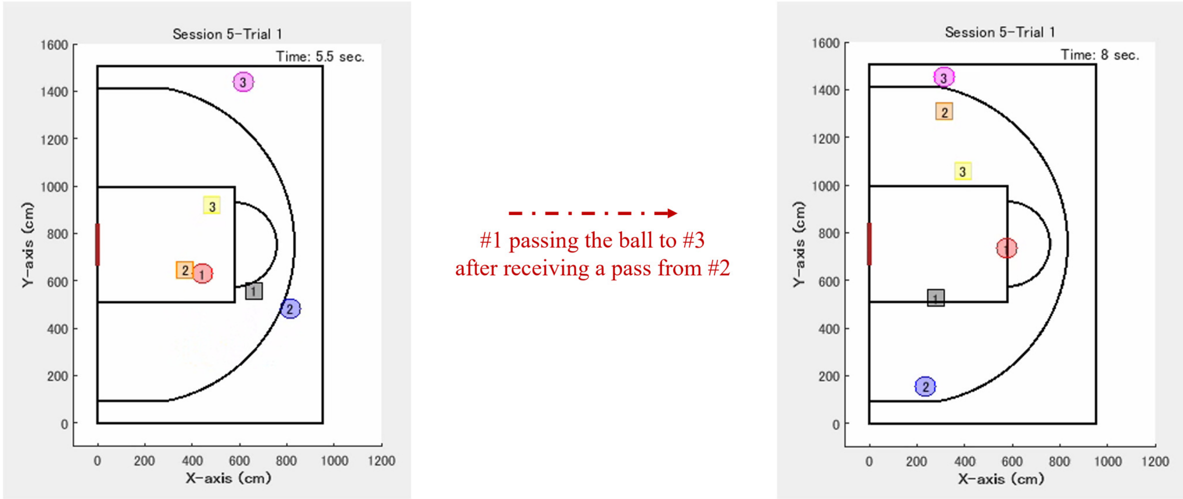

FIGURE 8
Typical example of offensive coordination after receiving the tips about the role of intervention decision and adjustment, observed in this practice. #1 runs toward the area under the basket goal ("paint area") and receives a pass from #2. Subsequently, #3 required for this role moves to the corner area while maintaining a reasonable distance from each defensive player, receives a pass from #1, and aims to take a three-point shot.

on coordination. In this practice, the results confirmed that in the bins of the relatively large distance between the participant required for the relevant role and each defensive player, the frequencies after receiving the tips of the crucial role were significantly higher than before (Figures 5B,C). Conversely, in the bin of the relatively small distance, the frequency after receiving these tips was significantly lower than before (Figure 5A). Furthermore, the winning rate on the offensive team improved temporarily (Figure 3); however, the effects of receiving the tips were not maintained. Therefore, these results partially supported the hypothesis regarding the effects of giving the tips.

After receiving the tips, the participant required for the offensive role of intervention decision and adjustment maintained a reasonable distance from each defensive participant. This suggests that the spacing skill might create favorable situations for coordination, such as moving to the corner area and aiming to take a three-point shot, as explained in Table 1 (Figure 8). Although the effect sizes and powers were lower for the distance with the other offensive players compared with those with the defensive players, notable trends were observed. In the bins of relatively small and large distances, the frequencies after receiving the tips of this role tended to be significantly higher than before (Figures 7A,C). In the bin of the middle distance, the converse result was obtained (Figure 7B). Such a U-shape trend might indicate that the participant required for the relevant role also stayed in place without interrupting the other offensive participants, as explained in Table 1. However, these discussions should be investigated in more detail. The previous studies in basketball suggested that offensive interactions, involving ball movement to an opposite side and maintaining a reasonable distance with a defensive player, create a gap with the opponent (16, 45). These lead to offensive shooting opportunities in open space. In this practice, running to the corner area can serve as a starting point for moving the ball to the opposite side. This enabled the participant required for the crucial role of taking a three-point shot in an open space. Therefore, such coordination increases the countermeasures for the defensive team, making it difficult to anticipate the next playing. Spacing skill, including a reasonable distance from the goal, is related to a high success rate of offensive shooting and defense in basketball. Expanding space within one's own team and limiting it for the opponent team to develop successful opportunities. These variables are key to predicting team performance using statistical and machine learning models [e.g., (13, 14, 16, 45, 46)]. It is also essential to create favorable situations in soccer other than basketball and influence strategies [e.g., (49, 50)]. The previous study (49) confirmed that the experimenter manipulated space to play in a soccer game and its limitations influence strategic behaviors. Another study (50) quantified and visualized the occupied space of each soccer player using applied geometric analysis with Voronoi diagrams. These results suggest that dynamical adjustment of defensive space according to situations limits opponent passing options. Although the types of team sports and methods used in these studies differed from those used in this study, the findings are similar to ours. Meanwhile, many previous studies mentioned above analyzed professional teams. Hence, our results from the female university team, which was affiliated with the third division league in Japan and did not have a high skill level, are valuable. Therefore, this study provides new insights into spacing skill related to the role of intervention decision and adjustment.

This study may also provide the results that satisfy the usefulness and ecological validity of the role of intervention decision and adjustment. Ecological validity is related to the problem that the experimental environment and observed actions significantly differ from real-world activities (51). However, after receiving the tips for this role, high offensive team performance could not be maintained in the final session (Session 6). This was caused by the defensive team establishing an effective countermeasure. After this practice, the experimenter asked the defensive team about it; the participants reported that defensive #3 marking the participant in the relevant role pretended to help the other players while actually kept marking. Thus, it was easy to establish the defensive countermeasure because the offensive pattern, as shown in Figure 8, was standardized. The offensive team had to flexibly handle the defensive one through bargaining based on the tips. However, the participants could not achieve developed coordination because of some factors, such as only a single practice and their individual skills corresponding to the third division league in Japan; they would need more training. Flexible coordination according to dynamic situations is required in various activities regardless of team sports (31, 52–54). Furthermore, both top-down and bottom-up information processing are crucial for coordination. The shared mental model of knowledge structures including strategies leads to efficient group interactions because the members can explain and anticipate actions from each other. A group also needs to fine-tune to a dynamically changing environment and others' unanticipated actions (55–57). Defensive coordination in 5-on-5 basketball games for the top-level university team in Japan shows that the structures of role-sharing switch according to emergent situations (1). In this practice, the offensive team established a shared mental model based on the tips of the crucial role. Although such top-down processing worked, developed bottom-up one might not be established in this team.

Future studies should mainly investigate (1) the number of teams participating in this practice, (2) the direct evaluation of spacing skill, and (3) these applications in other team sports. Regarding (1), only one female university team participated in this practice. The mini-games must be conducted for other teams with similar skill level. Furthermore, it is crucial to conduct the games for expert teams. The game requires basic coordinated behavior. Hence, if expert teams play it, they can express key strategies without the tips from a coach. Next as for (2), this study highlights the importance of spacing skill related to the role of intervention decision and adjustment. However, it is necessary to evaluate it directly. Similar to the previous study (50), applied geometric analysis with Voronoi diagrams enables the quantification and visualization of the occupied space of each player and the investigation of systematic offensive coordination with the player in this role. Additionally, analysis considering contexts, such as passing, dribbling, and shooting, is required [e.g., (13–16)]. These approaches develop deep discussions; it should be kept in mind that the results of this study indicate the overall trends of playing related to the particular role based on the experimental findings in cognitive science (21). In relation to (3), as mentioned above, spacing skill is also required in 5-on-5 basketball and soccer. Hence, if we develop a similar mini-game for other team sports, in which the relevant role is key, practical applications might be conducted. The academic and social impacts are significant because we provide an example of how to bridge the gap between controlled experiments and real-world applications. Therefore, our findings may contribute to practice design for the acquisition of spacing skill related to the relevant role and off-ball movements. Our work may offer implications for further developing 3-on-3 basketball itself. Similar to the experiment (49), a practice may be developed where the play range is limited, encouraging attention to space. For example, a coach can manipulate the offensive play range by changing the positions of defensive opponents. If a defensive player approaches to help another player, an offensive player in the role of intervention decision and adjustment role runs to a corner area and takes a three-point shot. Meanwhile, if a defensive opponent does not approach, the offensive player does not pass to this role but keeps dribbling to take a shot.

5 Conclusion

We applied the experimental findings in the cognitive science study of the crucial role in coordinated behavior of a triad through role-sharing to the field of sports as a pilot study. This study investigated the influence of the offensive role of intervention decision and adjustment on coordination in 3-on-3 basketball to discuss the usefulness of this role. The mini-game was developed, in which the relevant role is key, and introduced it to the practice of the female university team. The results showed that in the bins of the relatively large distance between the participant required for this role and each defensive player, the frequencies after receiving the tips of the mentioned role were significantly higher; the winning rate on the offensive team improved temporarily; however, the effects were not maintained. This suggests that spacing skill, which maintains a reasonable distance from each defensive player, emerged. Our study may provide the findings that satisfy the usefulness and ecological validity. These may bridge the gap between controlled experiments and real-world applications and contribute to practice design for the acquisition of such spacing skill and off-ball movements. In future work, it is important to examine the interactive structure to discuss the offensive coordination process.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Ethics statement

The studies involving humans were approved by the ethics and safety committee of Shizuoka University and Tokoha University. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study. Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

Author contributions

JI: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Software, Supervision, Visualization, Writing – original draft, Writing – review & editing. MY: Conceptualization, Formal analysis, Investigation, Methodology, Resources, Writing – review & editing. KF: Conceptualization, Formal analysis, Methodology, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fspor.2025.1513982/full#supplementary-material

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Application of association rules to ball possessions in professional men's football

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Introduction: This study represents one of the first attempts to apply association rule mining to the analysis of ball possession in professional men's football. The goal was to uncover hidden patterns among key tactical variables influencing possession success.

Methods: Using observational methodology, 2,324 ball possessions from the UEFA Euro 2020 championship were analyzed. The Apriori algorithm was applied to generate a total of 4,818 association rules, focusing on variables such as possession time, tactical intent, and field zones where possession occurred.

Results: The results show that short possessions, with the intent to progress and developed in advanced zones of the field, are strongly associated with successful outcomes. This is reflected in high lift values (up to 40) and strong confidence levels. In contrast, long possessions in offensive zones did not consistently correlate with success.

Discussion: These findings suggest that possession duration alone is not a reliable predictor of success. Instead, the combination of short possessions, in advanced zones, and with progressive intent, is more closely associated with positive outcomes. Association rule mining emerges as a valid and interpretable tool to support decision-making in elite football.

KEYWORDS

performance analysis, football, soccer, association rules, observational methodology

1 Introduction

A key aspect that differentiates performance analysis from other branches of Sports Sciences is its focus on studying athletes' actual behavior in their habitual environments, such as during competitions or training sessions (O'Donoghue, 2014). Traditionally, this evaluation has been conducted through observation, either in real time or by reviewing recordings with automatic devices and electronic models. Thus, performance analysis seeks to objectively, systematically, and specifically record the spontaneous behaviors of players and teams in context. By properly coding and analyzing these behaviors, it generates valid and useful results for advancing knowledge in the field.

In high-performance football, performance analysis is a relatively young scientific discipline (González et al., 2018). Despite significant progress in recent years, it has yet to reach full scientific maturity or provide coaches with precise information to enhance decision-making. Two macro-stages can be clearly distinguished in this field: an initial descriptive phase, where

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studies aimed primarily at documenting and explaining events during competition (McGarry, 2009); and a subsequent comparative and predictive stage, which incorporates theoretical models to anticipate behaviors within the game context (Memmert and Rein, 2018).

At the end of the 20th century and the beginning of the 21st, the dominant method for describing performance was "quantitative assessment," based on frequency calculations and event descriptions. For instance, studies such as Barros et al. (2007) analyzed distances covered by different players, while Dellal et al. (2011) examined technical performance. Wallace and Norton (2014) characterized gameplay based on execution speed and various technical patterns, and Gréhaigne et al. (2001) explored playing space and player movement zones from a qualitative perspective.

With the integration of new statistical and technological tools, the vast amount of data generated in competitions necessitated more sophisticated analysis approaches. This led to the use of association and independence analyses to determine relationships between key variables. For example, Oliva-Lozano et al. (2023) identified that the first 15 min of each half produced the highest frequency of maximum-speed actions; Martínez-Hernández et al. (2023) found associations between goal-scoring and prior movements; and Clemente et al. (2023) established links between coaches' nationalities and training methods. A particularly notable study by Teoldo and Cardoso (2021) demonstrated a statistical relationship between a player's birth month and the likelihood of becoming a professional footballer. This statistical development has led to a significant advance in football performance research, uncovering associations between categorical variables that were previously difficult to quantify.

The emergence of "dynamic tactical assessments" or "match analysis 4.0" (Memmert and Rein, 2018) in 2011 marked a new phase, incorporating advanced techniques such as machine learning. These approaches enable predictive modeling of in-game events Cohen (1960). Nunes et al. (2020) using GPS data found that larger playing areas with a high number of players involved promoted high-intensity movement, while smaller areas allowed to reduce the pace of play, in addition to facilitating more technical actions such as dribbling, blocking or interceptions; in another study of a similar nature (Nunes et al., 2021) they showed that playing in situations of high inferiority (such as 4vs2) can increase the physical demand of the team in numerical inferiority; Iván-Baragaño et al. (2024) analyzed the evolution of technical and tactical aspects in women's football, and Immler et al. (2021) examined coaching styles. Wright et al. (2011) applied binary logistic regression to demonstrate that goalkeeper positioning and shot type are directly associated with goal outcomes.

Given these advancements, it is clear that analytical techniques have driven a paradigm shift in football science. However, despite their widespread adoption among researchers, continued innovation remains crucial. One underexplored technique is association rule mining, a key method in data mining (Han and Fu, 1995; Han and Pei, 2000) used to identify hidden relationships within large datasets (Imielinski, 1996). Association rules, also known as affinity rules, uncover frequent patterns that co-occur, offering valuable insights for decision-making.

Association rule mining is based on three fundamental measures: support, confidence, and lift. Support refers to the proportion of instances where two or more elements appear together (e.g., a transaction contains X, Y, and Z). Confidence measures the conditional probability that an item appears given the presence of another (e.g., if X and Y occur, Z is also likely to occur). Lift evaluates the strength of this relationship relative to random chance: Lift > 1 indicates a positive association (items co-occur more often than expected by chance), Lift < 1 indicates a negative association, and Lift = 1 suggests no association. These metrics enable the identification of meaningful patterns that can inform tactical and strategic decision-making.

In sports research, association rule mining has been scarcely applied (Stein et al., 2017), despite its potential for analyzing chaotic and unpredictable environments like football. Given the dynamic interactions between players, examining large datasets can reveal crucial tactical combinations that influence match outcomes. By identifying recurrent patterns in play sequences, coaches can optimize their strategies against various opponents. This is particularly valuable in football, where minor tactical adjustments can yield significant advantages. Furthermore, association rules can aid in anticipating opposing teams' strategies, providing a data-driven competitive edge.

Considering the above, applying association rule mining to team sports analysis is a promising and methodologically sound area of research. Investigating temporal associations in football data could enhance our understanding of tactical dynamics, leading to scientifically backed recommendations for performance optimization. Consequently, this study aims to analyze possession-based interactions in high-performance football, identifying recurring patterns and systematic behaviors to contribute to the growing body of knowledge in this field.

2 Materials and methods

2.1 Design and participants

For the development of this study, the observational methodology was used (Anguera, 1979), a methodology that has proven to be one of the most suitable for studying the spontaneous interaction behavior among athletes, including its mixed-methods approach (Castañer et al., 2013). The design of this research is punctual—intrasessional follow-up—multidimensional, and nomothetic (Anguera et al., 2011). It should be noted that the observation is governed by scientific criteria, with full observer perceptivity and a non-participant observer.

To select the participants, an intentional or convenience a convenience sampling method was used (Anguera et al., 2011). Ball possessions during the final phase of the UEFA EURO, specifically the 2020 edition, were collected and analyzed. In total, 2,324 ball possessions were examined. The inclusion criteria proposed by Garganta (1997) were followed. Additionally, extra time periods were excluded, as they were considered special situations. The exclusion of extra time was based on ensuring homogeneity in the competitive context. In tournaments such as UEFA Euro 2020, not all matches include extra time, which introduces structural variability that affects data comparability. Extra time is generally influenced by situational factors such as accumulated fatigue, strategic game management, or the likelihood of a penalty shootout. Therefore, its inclusion would have introduced contextual bias. However, it is also acknowledged that excluding extra time may omit critical moments that can affect match outcomes, potentially reducing the applicability of the findings.

Data collection was conducted using publicly available footage broadcast on television, of general interest and sponsored by various private entities.

TABLE 1 Observation instrument.

	Criteria	Categories	Description
1	Half time (match part)	First half Second half	This criterion refers to whether the possession occurs in the first or second half of the match.
2	Start form	Transition Set piece	This criterion refers to whether the possession begins in transition (with the ball in play) or through a set-piece action.
3	(COI) Interaction context	AR: forward versus delayed line AM: forward versus middle line AA: forward versus forward line MM: middle versus middle line MR: middle versus delayed line MA: middle versus forward line RA: delayed versus forward line RM: delayed versus middle line PA: goalkeeper versus forward line	This criterion refers to which line recovers the ball and against which opposing line: AR (forward vs. delayed line), AM (forward vs. middle line), AA (forward vs. forward line), MM (middle vs. middle line), MR (middle vs. delayed line), MA (middle vs. forward line), RA (delayed vs. forward line), RM (delayed vs. middle line), PA (goalkeeper vs. forward line).
4	Intention	Progress Keep	This criterion refers to the tactical intention of the team: to progress (when the team clearly and intentionally advances toward the opponent's field by making at least two forward passes or sending the ball to the penalty area), or to stay (when the team clearly and intentionally does not advance with the ball, plays laterally, or the first two passes are made backward).
5	MD		This criterion refers to the time the observed team maintains ball possession in its defensive zone.
6	MO		This criterion refers to the time the observed team maintains ball possession in its offensive zone.
7	ZC		This criterion refers to the zone in which the team maintained possession for the longest time.
8	Time possession		This criterion refers to the total duration of ball possession.
9	Passes		This criterion refers to the total number of passes made by the team in possession of the ball.
10	Move outcome	Goal scored Shot on goal Send to area No success	This criterion refers to the outcome of the ball possession: goal (goal scored), shot (shot on goal), sending to the area (ball sent into the opponent's area), or no success (no significant outcome).
11	Match status	Winning Drawing Losing	This criterion refers to the partial match status at the time of possession (winning, drawing, or losing).
12	Final score	Win Draw Lose	This criterion refers to the final result of the match for the team in possession (win, draw, or loss).

Source: Maneiro et al. (2020).

2.2 Observational instrument

To carry out this work, the observational instrument proposed by Maneiro et al. (2020) (Table 1) was used, given its effective molar-molecular fit in collecting this type of data, as demonstrated in similar studies on men's football. The observational instrument is a combination of field format and category systems (Anguera et al., 2007), being nested within the various field formats.

2.3 Registration and coding

The data recording (Hernández-Mendo et al., 2014) was conducted using the Lince Plus program (Soto et al., 2019). Inter-observer agreement was analyzed by pairs, generating all six possible combinations between the four observers (Ob1–Ob2, Ob1–Ob3, Ob1–Ob4, Ob2–Ob3, Ob2–Ob4, and Ob3–Ob4). The average Kappa value obtained was 0.92, which is classified as very good according to the scale proposed by Fleiss et al. (2003). Four observers were selected for data collection, all of whom hold doctorates in Sports Sciences and are UEFA PRO-licensed coaches. Additionally, to ensure the quality of the methodological process, a methodologist expert in observational methodology also participated in the study. Although formal blinding was not implemented, observer bias was minimized through strict adherence to standardized training protocols, including eight preparatory sessions, individual calibration phases, and collective discussion of discrepancies.

Before the coding process and to reduce variability among observers, eight training sessions were conducted, following Anguera et al. (1999). Each training session lasted 2 h. The first three sessions were conducted in a group with the selected observers. During these sessions, the study was presented theoretically, player behaviors to be observed were defined, the observational instrument was introduced, and the observers were trained in using the Lince Plus recording tool. In the fourth session, observers participated in observing and recording 20 pre-selected offensive actions, organized from least to most complex by the principal investigator. After recording the actions, discrepancies were discussed. The fifth and sixth sessions were conducted individually with each observer. The initial delimitation of the recorded actions was performed by the principal investigator, and observers received instruction on how to record the actions. The last two training sessions were also conducted individually, during which Cohen's Kappa coefficient of agreement was verified between the principal investigator and each observer. Ten percent of the total sample ($n = 233$) was used to assess data quality. Although formal blinding was not implemented, observer bias was minimized through strict adherence to standardized training protocols, including eight preparatory sessions, individual calibration phases, and collective discussion of discrepancies. This methodological rigor ensured consistency and objectivity in the coding process.

2.4 Data analysis

For statistical analysis, R version 4.3.1 was used with the libraries arules, arulesViz, and RColorBrewer. Specifically, the arules package (version 1.7–7), titled *Mining Association Rules and Frequent Itemsets*, was used. The URL is https://cran.r-project.org/src/contrib/Archive/arules. The arulesViz package (version 1.5–2), titled *Visualizing Association Rules and Frequent Itemsets*, was also used (URL: https://cran.r-project.org/web/packages/arulesViz). Finally, the RColorBrewer package (version 1.1–3) was used (URL: https://cran.r-project.org/web/packages/RColorBrewer/). Association rules, a branch of artificial intelligence (AI), were employed to identify general "if-then" patterns, applying specific criteria to define key relationships. This type of analysis does not test causation but simply identifies temporal associations. Nevertheless, it is useful for establishing hypotheses that can later be analyzed in greater depth. Additionally, it does not rely on correlation and does not imply causation. Within a given timeframe, once an event is associated with another, this relationship may vary on different occasions.

It is an unsupervised learning technique used to extract relevant information from large datasets. Each association rule is linked to various numerical measures that determine its relevance. Its primary strength lies in interpretability, which is increasingly valued in the field of machine learning. The basic concepts of association rules include items, understood as the elements that make up a transaction, and itemset, defined as a set of elements within a transaction.

Measures such as *support*, *confidence*, and *lift* are used. *Support* indicates the popularity of an item, measured by the proportion of transactions in which a set of items appears. *Confidence* indicates the probability that item Y occurs when item X has already occurred, expressed as {X = > Y}. This is measured by the proportion of transactions with item X in which item Y also appears. Finally, *lift* is the ratio between the observed support and what would be expected if X and Y were independent (Table 2).

In the context of football, lift values above 1.2 may indicate meaningful associations when accompanied by sufficient support and confidence. Values exceeding 1.5 can be considered tactically relevant, while lift values over 2 point to strong associations far from randomness (Stein et al., 2017).

The structure of the association rules (i.e., the allocation of antecedents and consequents) was determined automatically by the Apriori algorithm based on item frequency and co-occurrence, subject to minimum support and confidence thresholds. However, the selection and codification of the input variables were theory-driven and based on domain relevance in football performance analysis. In practice, this means that while Apriori algorithmically generated the rules, the set of possible items was predefined through a observational instrument.

TABLE 2 Formula of the association rules indicators.

$\text{Support (X= > Y)} = \dfrac{\text{Number of transactions containing both X and Y}}{\text{Total number of transactions}}$
$\text{Confidence (X= > Y)} = \dfrac{\textit{Number of transactions containing both X and Y.}}{\textit{Number of transactions containing X}}$
$\text{Lift (X= > Y)} = \dfrac{\text{Confidence}(X => Y)}{\text{Support}(Y)}$

This manuscript retains the notation = > to represent the relationship between antecedents and consequents in association rules, in line with the output format of the arules package in R, which is widely used in data mining.

Subsequently, the "*A priori*" algorithm is used, which leverages prior knowledge of frequent properties within the dataset. It is applied to identify frequent itemsets.

3 Results

The "A priori" algorithm is applied (Figure 1), and the fundamental qualitative measures are obtained to identify the association rules. The items used are: HalfTime, StatForm, COI, Intention, MD, MO, ZC, Time Possession, Passes, Move Outcome, MatchStatus, and Final Score.

The output corresponds to the execution of the Apriori algorithm in R for association rule mining, using the arules package. The main parameters are specified: minimum confidence level of 80%, minimum support of 2%, and a maximum of 10 generated rules. The dataset includes 1,196 transactions and 260 items, of which 94 were recoded to optimize the analysis. The transaction tree structure is successfully created, verifying subsets of size 1 to 7. As a result, 4,818 association rules were generated, with a minimum absolute support threshold of 23 transactions. Algorithmic controls such as filtering, sorting, and memory storage are applied. Finally, the process concludes with the creation of the S4 object that stores the obtained rules.

In this case, a minimum support of 0.02, a minimum confidence of 0.8, and a number of elements between 1 and 10 were set to generate association rules. Under these conditions, 4,818 rules were obtained and then subjected to a pruning process to improve clarity and analytical value. Specifically, four steps were followed: (1) elimination of redundant or semantically overlapping rules, given the high dimensionality of the dataset (260 items derived from 1,196 transactions); (2) application of a secondary filter prioritizing rules with a lift > 1 to ensure stronger-than-random associations; (3) contextual filtering to remove rules lacking football-specific tactical relevance; (4) final selection based on lift and support values to retain the most interpretable and meaningful patterns. Figure 2 presents the final result, where the specific values of support and confidence may exceed the initially defined minimum thresholds.

```
Apriori

Parameter specification:
 confidence minval smax arem  aval originalSupport maxtime support minlen
        0.8    0.1    1 none FALSE            TRUE       5    0.02      1
 maxlen target  ext
     10  rules TRUE

Algorithmic control:
 filter tree heap memopt load sort verbose
    0.1 TRUE TRUE  FALSE TRUE    2    TRUE

Absolute minimum support count: 23

set item appearances ...[0 item(s)] done [0.00s].
set transactions ...[260 item(s), 1196 transaction(s)] done [0.00s].
sorting and recoding items ... [94 item(s)] done [0.00s].
creating transaction tree ... done [0.00s].
checking subsets of size 1 2 3 4 5 6 7 done [0.00s].
writing ... [4818 rule(s)] done [0.00s].
creating S4 object  ... done [0.00s].
```

FIGURE 1
Application of the Apriori algorithm. Schematic representation of the application of the Apriori algorithm in this study. The diagram outlines the analytical workflow from the coding of ball possessions to the generation of 4,818 association rules, specifying the parameters used (minimum support of 2%, minimum confidence of 80%, and a maximum of 10 items per rule). It also illustrates the transformation of data into transactions and the rule selection process.

	lhs		rhs	support	confidence	coverage	lift	count
[1]	{5, 6}	=>	{3}	0.004302926	0.9090909	0.004733219	1.201779	10
[2]	{2, 5, 6}	=>	{3}	0.004302926	0.9090909	0.004733219	1.201779	10
[3]	{1, 5, 6}	=>	{3}	0.003872633	0.9000000	0.004302926	1.189761	9
[4]	{1, 2, 5, 6}	=>	{3}	0.003872633	0.9000000	0.004302926	1.189761	9
[5]	{5}	=>	{3}	0.096815835	0.8893281	0.108864028	1.175653	225
[6]	{2, 5}	=>	{3}	0.094664372	0.8870968	0.106712565	1.172704	220
[7]	{1, 5}	=>	{3}	0.094664372	0.8870968	0.106712565	1.172704	220
[8]	{1, 2, 5}	=>	{3}	0.092512909	0.8847737	0.104561102	1.169633	215
[9]	{5, 7}	=>	{3}	0.021084337	0.8750000	0.024096386	1.156712	49
[10]	{2, 5, 7}	=>	{3}	0.021084337	0.8750000	0.024096386	1.156712	49
[11]	{4, 5}	=>	{3}	0.081755594	0.8715596	0.093803787	1.152164	190
[12]	{1, 5, 7}	=>	{3}	0.020223752	0.8703704	0.023235800	1.150592	47

FIGURE 2
Qualitative measures. Visualization of the qualitative measures derived from the Apriori algorithm. The specific support, confidence, and lift values that characterize the selected rules are shown. These metrics allow for the identification of relevant associations between tactical variables, and are key criteria for selecting the most significant rules in the analysis. The coding in the LHS column corresponds to the variables collected in the observation tool (Table 1), following the same numerical order of presentation.

The criterion used to select association rules in this case is a lift greater than 1, indicating that the items are positively related.

Therefore, the first twelve rules meet this requirement. In this study, we selected the first two rules showing the highest values. The first association rule links the items MD and MO with the item COI, with a lift of 1.20. The second association rule links the items StartForm, MD, and MO with the item COI, also with a lift of 1.20.

The established relationship includes the Start Form variable, which can occur either through a ball steal (a change in ball possession from one team to another via a turnover) or a regulatory incident (such as a set play). Once the ball is recovered (Start Form), possession begins in the team's own half (MD), after which they can progress and establish possession in the opponent's half (MO). As with the previous scenario, the longer the possession lasts, the higher the chances for the various lines or interaction contexts to emerge.

A 2D graphical visualization (Figure 3) displays 4,818 association rules using color-coded bubbles: darker colors represent higher Lift values (stronger relationships), and larger bubble sizes indicate higher Support (frequency). This visual format helps to easily interpret the relationships between antecedents and consequents.

Three main groups of rules stand out:

- 15 rules include MD = 2 and ZC = 2, plus two other items, predicting that "time of possession" will be 2. These rules have high Lift values, indicating strong associations, and are shown with darker bubbles.

- 8 rules include MO = 6 and MD = 0, plus two additional items, predicting a "time of possession" of 6. Although fewer, these rules also show strong associations due to their high Lift.
- 3 rules include MO = 10 and MD = 0, with one more item, predicting a "time of possession" of 10. Despite being the smallest group, they are very relevant because of their strong Lift values.

These three groups were identified computationally during rule generation and are represented in Figure 3 as visually clustered bubbles with similar support and lift characteristics. Although individual rules are not labeled in the figure, their grouping is reflected through bubble proximity and color.

Notably, some rules in the dataset reach extremely high Lift values (above 30 or even 40) which, in the context of association rule mining, indicate exceptionally strong and non-random associations. In football terms, such high lift suggests that the co-occurrence of certain tactical elements (in this case, the teams' tactical objective during ball possession is to advance toward the opponent's goal, that is, they seek to implement building strategies that allow vertical progression toward the opposing goal) is far more likely than expected by chance, revealing stable and recurrent patterns in high-performance play.

This visualization, based on Support and Lift, clearly highlights the most relevant patterns in the dataset, making the analysis more intuitive and easier to interpret. The tactical aim of teams during ball possession is to advance toward the opponent's goal, meaning they seek to implement building strategies that enable vertical progression toward the opposing goal.

On the other hand, the rule with the highest Support comprises 412 rules formed by the antecedents COI = 1 and Passes = 0, with MD = 0 as the consequent, along with 22 additional items. Although this rule is not the focus of analysis, it provides insight into the items with the highest frequency.

4 Discussion

This study was conducted with the objective of analyzing possible relationships established during ball possessions in high-performance football, aiming to identify regularities or general behavior patterns. To achieve this goal, a novel statistical technique in the field of sports performance (association rules) was implemented.

Firstly, the algorithm generated 4,818 association rules across 2,324 ball possessions (Figure 1), indicating a high volume of patterns or temporal associations. These associations suggest the existence of hidden relationships among the variables considered during ball possessions that frequently appear in matches. Football is a sport characterized by collaboration and opposition, shared space and simultaneous participation, where different game structures at the micro (1vs1, 2vs2), meso (3vs3, 4vs4, 5vs5.) and macro (11vs11) levels are interconnected and can behave as superorganisms (Duarte et al., 2012). Performance in these team sports arises from interactions, where the actions of a player or group of players are a result of interpersonal relationships between teammates and opponents (Santos et al., 2018). Furthermore, these interactions between players can give rise to both individual and collective technical behaviors, such as sprints, dribbles, blocks, or even promoting variability in the number of passes.

On the other hand, in Figure 2, the available data show that the relationship between the variables MD, MO = > COI indicates that these elements appear together more frequently than they would by chance, establishing a positive relationship. The criterion used for selecting the association rules in this case is a lift greater than 1. This signifies a positive relationship between the antecedent and the consequent, with a lift of 1.20 alongside high confidence and support. The RHS (Right-Hand Side) shows that in this combination of associations in football, the variable COI is always present. Specifically, in football terms, it can be asserted that increased possession time in either offensive or defensive sectors correlates with more associations occurring within particular lines or interaction contexts (Castellano, 2000). This confirms that teams establish connections among the different lines set up tactically (Kannekens et al.,

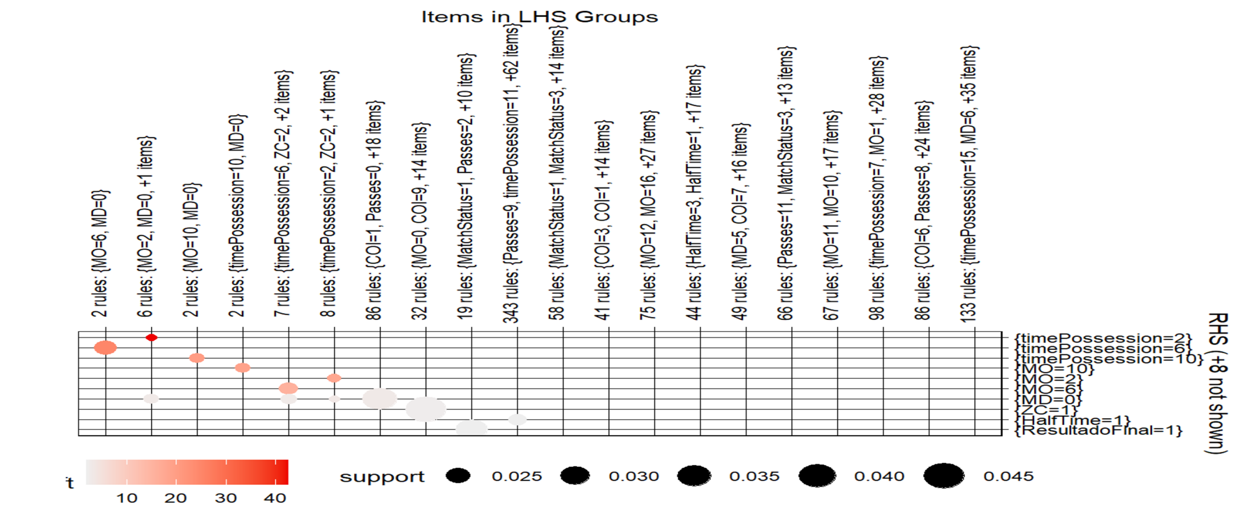

FIGURE 3
Grouped matrix of 4818 rules. Grouped matrix of 4,818 association rules generated using the Apriori algorithm. The horizontal axis represents the sets of antecedents (lhs), and the vertical axis shows the consequents (rhs). Each circle represents a rule, with its size indicating support (relative frequency) and its color indicating the lift value (strength of association). More intense colors reflect stronger associations between items.

2009; Wiemeyer, 2003). Regarding the possession zone, while not explicitly concluded from these results, we may predict that longer possession time correlates with a higher number of goals and overall success (Casal et al., 2017; Collet, 2013).

To aid the tactical interpretation of the MD, MO = > COI rules, it is important to clarify that MD refers to the time of possession in the defensive midfield, MO to the time of possession in the offensive midfield, and COI to the context of interaction between the recovering line and the opposing line. Thus, a rule with MD and MO as antecedents and COI as the consequent—especially with a lift greater than 1—suggests that maintaining possession across both midfield zones is frequently linked to specific interaction dynamics. This implies coordinated progression behavior across lines, which has tactical relevance. Moreover, high lift values (some exceeding 30 or 40) reflect extremely strong and non-random associations between tactical events. In football terms, a lift of 2 already indicates that the co-occurrence of two elements is twice as likely as by chance, and values above 1.5 may be considered tactically meaningful when supported by adequate confidence and support levels.

From the same figure, a connection between the variables Start Form, MD, and MO = > COI is also evident, showing a lift of 1.20. This relationship involves the variable Start Form, which can result from a ball recovery (a turnover where possession shifts from one team to another) or a regulatory event (such as a set piece). Following a ball recovery (Start Form), possession typically begins in the team's own half (MD) before transitioning into the opponent's half (MO). Similar to the previous case, an extended possession duration is associated with a higher likelihood of interactions across different tactical contexts. This occurs as the team progresses toward the opponent's goal in pursuit of scoring, necessitating coordinated actions among teammates and defensive responses from the opposing side (Maneiro et al., 2019; González-Ródenas et al., 2021).

The grouped matrix presented in Figure 3 also reveals interesting results that align with the previous ones. The association with the highest intensity consists of 6 rules with MO = 2 and MD = 0, and is always accompanied by RHS equal to 2, corresponding to the "time possession" variable, with a high lift of 40. The second most interesting association appears in the first column, with 2 rules having MO = 6 and MD = 0. Again, these results confirm the earlier findings about the strong association between possession time in both defensive and offensive midfield and total possession time, but this time with a strong association evident from the lift value (30). This allows us to state that possession time in either of the two areas of the field determines total possession time, data that aligns with previous work on possession analysis in high-performance football (Link and Hoernig, 2017).

Although the present study applied association rules to discover frequent and significant patterns in ball possession sequences, it is important to situate these findings within the broader landscape of methods used in soccer performance analysis. Previous research has employed techniques such as regression analysis to identify and categorize playing styles in elite teams (Fernandez-Navarro et al., 2018), as well as to predict outcomes based on performance indicators (Liu et al., 2013). On the other hand, unsupervised clustering techniques and big data approaches have been used to identify situations and behaviors in football matches, allowing for a more detailed segmentation of game dynamics (Michael et al., 2018; Rein and Memmert, 2016). Compared to these methods, association rules offer an alternative perspective, by highlighting non-linear and multivariate co-occurrence patterns that may go unnoticed in models that require predefined outcomes or assume independence between variables. Therefore, this study contributes to the field by introducing an approach that allows detecting emergent tactical structures from combinations of frequent items, thus enriching the set of methodological tools available in the analysis of football performance.

Beyond post-match analysis, the association patterns identified in this study could be applied in real-time tactical decision-making. For instance, if during a match the coaching staff observes repeated sequences involving short possessions initiated in the offensive midfield and ending in the attacking third, they could recognize this as a favorable pattern previously linked to effective outcomes. This awareness could inform on-the-fly decisions such as adjusting pressing intensity, modifying player roles, or reinforcing vertical attacking transitions. These insights could also support pre-match planning, helping coaches design training drills that replicate high-impact patterns identified through association rules, thereby bridging data analysis with applied tactical practice.

At the applied level, and from a coaching recommendation perspective, the patterns identified through association rules can be valuable tools for coaches in different training contexts. In task design, the most frequent and strongly associated behaviors, such as short possessions initiated in attacking midfield with the intent of progressing, can be used to structure drills that replicate these successful sequences. Regarding opponent analysis, coaches and analysts can look for recurring possession patterns employed by the opponent and compare them with the favorable or unfavorable rules identified in this study, thereby adjusting the match plan.

Despite its contributions, the present study has limitations. Association rule mining does not infer causality, and interpreting a large number of generated rules can be complex. Additionally, the analysis was based exclusively on a single tournament (UEFA Euro 2020), which limits the generalizability of the findings. Applying this method to other competitions—such as national leagues or World Cups—would help validate and expand the applicability of the approach. Moreover, the inclusion of extra time was excluded to maintain contextual consistency, although this may omit decisive phases of the match. The exclusion was based on structural heterogeneity: not all matches involve extra time, and when it does occur, it is heavily influenced by fatigue, strategic management, or the likelihood of penalty kicks. Nevertheless, this may reduce the ecological validity of the analysis.

Furthermore, several contextual variables were not included in the model, such as individual player actions, referee decisions, crowd influence, or environmental conditions. Future research should integrate these factors to enrich the complexity and ecological validity of tactical analysis. Also, it would be relevant to explore how individual possessions (e.g., by player roles or positions) interact within collective sequences. In addition, association rule mining could be applied to different formations or opponent strategies, and combined with other machine learning methods for predictive modeling. Finally, we encourage future research to explore the application of this method in women's football, contributing to the growing field of gender-informed performance analysis.

5 Conclusion

This study highlights the usefulness of association rule mining in analyzing ball possession patterns in high-performance football. The application of this method allowed for the identification of frequent, interpretable, and tactically relevant relationships between contextual variables, offering a detailed view of how certain combinations of play behaviors tend to co-occur.

The technique proved to be valuable due to several strengths: a high volume of generated rules (4,818), internal consistency across clusters of rules, and alignment with well-established tactical principles—such as short possessions initiated in the offensive midfield with the intention to progress. These factors support the validity of association rules as a method for capturing meaningful patterns, and their reliability is reinforced by the recurrence of consistent rule groups throughout different combinations of antecedents and consequents.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent from the patients/participants or patients/participants legal guardian/next of kin was not required to participate in this study in accordance with the national legislation and the institutional requirements.

Author contributions

RM: Conceptualization, Data curation, Investigation, Writing – original draft. MA: Data curation, Supervision, Methodology, Writing – review & editing. JL: Formal analysis, Methodology, Writing – review & editing. GJ: Methodology, Supervision, Validation, Writing – review & editing. AA: Conceptualization, Validation, Writing – original draft. II-B: Conceptualization, Data curation, Investigation, Supervision, Writing – original draft.

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Generative AI statement

The authors declare that no Gen AI was used in the creation of this manuscript.

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Comparison and association of performance indicators according to set outcome and set score difference in AVP women's beach volleyball

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Purpose: This study aimed to analyze the association between technical-tactical performance indicators and the set outcome, game phase, and set score difference.

Methods: In total, 41 matches, 79 sets, and 14,959 game actions [serve: 2,879; serve reception: 2,567; set: 2,176; attack (side-out): 2,324; block: 818; dig: 1,684; set (counterattack): 1,224; and counterattack: 1,287] from two women's Association of Volleyball Professionals Gold Series tournaments were analyzed. The independent variables were set outcome (i.e., winner or loser) and set score difference, whereas the dependent variables were points scored in each game phase, performance coefficient, and efficiency. A two-way analysis of variance was employed for comparison purposes and logistic regression was used to analyze the association between the match outcomes and the performance indicators.

Results: Winners scored more points in the K0, K2, and K3B game phases compared to losers. Similarly, higher performance coefficients and efficiencies were observed for actions performed during the defensive phase (block, dig, set, and counterattack). Moreover, the performance during the K2 and K3B phases, attack and counterattack efficiency, and the block and dig performance coefficients were associated with winning the set. The set score difference was characterized as an indicator of set balance because the differences in performance indicators between the winners and losers generally increased with greater point differentials.

Conclusion: In the context of elite women's beach volleyball, although attacking was important for winning a set, the key performance indicators were mainly derived from the construction of counterattacks. In addition, the set score difference reflects the balance of the set. Therefore, these parameters can be used to guide training programs and assess team performance.

KEYWORDS

game actions, performance coefficient, sand sports, notational analysis, team performance, key performance indicators

1 Introduction

Beach volleyball is one of the most popular Olympic sports in the world, with players competing in numerous events worldwide. The Association of Volleyball Professionals (AVP) organizes tournaments around the United States for athletes of different performance levels [i.e., athlete tiers (1)], of which the "Gold Series" events comprise the most elite athletes. In general terms, teams comprise two players, who try to score 21 points, with a difference of two or more points (i.e., 2-0) to win the set (15 points in the third set). During a rally, players exert intense effort to perform jumps and quick movements on the sand and recover in the intervals between rallies (2–4). However, the match outcome is mainly determined by technical-tactical performance. In this context, match analysis is a valuable tool for identifying key performance indicators.

Using this approach, beach volleyball match analysis commonly focuses on the set rather than the match as a whole (5–6). This leads to a more accurate analysis because the score from the first set is not carried over to the next (7). In each set, each point is played in a rally (i.e., the period between the serve and the ball going out of play), and some game phases are characterized according to ball possession. Thus, K0 denotes a serve; K1 (side-out) denotes a serve reception, a set, and an attack; and K2 denotes a block, a dig (i.e., the action of defending an attack), a set, and a counterattack. In addition, depending on whether the ball remains in play after the previous phases, K3A (consisting of a counterattack by the team that performed actions in K1) and K3B (consisting of a counterattack by the team that performed actions in K2) can also occur [adapted from (6, 8)]. The consideration of specific skills related to beach volleyball fundamentals and game phases allows for the identification of technical-tactical performance indicators that can help coaches and players achieve better game performance and understanding.

Previously, performance indicators have been investigated as a function of the set outcome in beach volleyball (6, 9). These indicators can be studied in absolute terms (e.g., the number of points scored) or in standardized terms [e.g., attacking efficiency (10)]. In this sense, the insights provided by Medeiros et al. (6) suggest that the coefficient of performance and counterattack are the key to winning a set at the U19, U-21, and senior levels. However, the competitiveness of a set, in terms of teams playing at an equal level, was not considered by the authors in this study. One way of quantifying the set balance is to examine the point difference between the winning and losing teams (9). Recently, Giatsis et al. (9) reported that attack percentage was a relevant predictor of winning a set, and serve points were also associated with set victories. Although this study provides robust insights, some limitations should be highlighted. The authors did not consider specific beach volleyball game phases (e.g., K0 or K1), and a performance coefficient (i.e., the average score adjusted for efficiency of actions) was not calculated, which could provide valuable information about the relationship between all actions performed within each fundamentals-specific skill. Additionally, the difference in set scores (i.e., the winner's points minus the loser's points) can help to understand the effect of score balance on performance indicators.

Therefore, the purpose of this study was to analyze technical-tactical performance indicators in terms of the set outcome, game phase, and set score difference. The primary hypothesis of this study is that the performance indicators of the winning team for attacking actions and in the counterattack phase will exceed those of the losing team, irrespective of the set score difference. Furthermore, we predict that the magnitude of the performance indicator difference between the two teams will diminish as the set becomes more balanced. The data presented herein will assist athletes and coaches in comprehending the variables that influence the set outcome in high-level women's beach volleyball.

2 Materials and methods

2.1 Match samples

The sample included 41 matches with 79 sets and 14,959 game actions [serve: 2,879; serve reception: 2,567; set: 2,176; attack (side-out): 2,324; block: 818; dig: 1,684; set (counterattack): 1,224; and counterattack: 1,287]. Nine sets were excluded because of a failure in the recording. The game actions were collected from two women's 2022 AVP Gold Series tournaments [Atlanta Open ($n = 18$; 43.90%), and Manhattan Beach Open ($n = 23$; 56.10%)] using official broadcasts available on YouTube. The third set of each match was not considered because the number of points to win the set differed from the first and second sets (i.e., 15 points vs. 21 points).

2.2 Characterization of the players

The match analyses included 25 beach volleyball teams. All the players who participated in these tournaments were at least "Highly Trained" following McKay et al.'s classification (11). The procedures were approved by a local ethics committee (Human Research Ethics Committee, Health Sciences Centre, Federal University of Paraiba; Opinion no. 4.360.235), and the Declaration of Helsinki was followed.

2.3 Variables and instruments

The set outcome and the set score difference were used as independent variables. The set outcome was split into a winner or a loser according to the final set score. The set score difference was classified using a two-step cluster analysis (distance measure: log-likelihood; clustering criterion: Bayesian information criterion). This approach was used to classify the set score difference based on the point difference between the winning and losing sets. Thus, a "large difference" (LD) was characterized by a difference of over 9 points; a "medium difference" (MD) was a difference between 6 and 9 points; and a "small difference" (SD) was a difference between 2 and 5 points.

The frequency of each cluster was as follows: LD = 9 sets (11%), MD = 25 sets (32%) and SD = 45 sets (57%).

Concerning the dependent variables, the efficacy score of game actions was classified according to Palao et al. (10). The serve, attack, and block actions were classified into five categories: 0—error (direct point to the opponent), 1—maximum opponent attack options (allowed the opposition the maximum number of options for a counterattack), 2—team limited attack options (allowed the opposition to conduct a limited counterattack), 3—no opponent attack options (does not allow a counterattack formation), and 4—scored points. Furthermore, the serve reception, dig, and set were classified in four categories: 0—error (point to the opponent), 1-no attack option (the opponent regained possession of the ball), 2—limited attack option (allowed perform a limited counterattack), and 3—maximum team attack options (maximum options for a counterattack).

The technical-tactical variables were calculated as follows:

- The points scored during the five game phases [adapted from (6, 8)]. Thus, K0 included points scored by serve; K1 (side-out) included the points scored after receiving the serve and attacking; K2 included points scored by blocking and counterattacking; K3A and K3B were the subsequent points scored by teams in the rally after K1 or K2, respectively. Moreover, the sum of points obtained in counterattacks was calculated (counterattack points = K2 + K3A + K3B).
- The performance coefficient was calculated using Coleman's equations (12). Thus, the equation $PC^{\text{continuous actions}}$ = [(1 × "n" efficacy score) + (2 × "n" efficacy score) + (3 × "n" efficacy score 3)/total of actions] was used to calculate continuous actions (i.e., serve reception, set, and dig), and $PC^{\text{terminal actions}}$ = [(1 × "n" efficacy score) + (2 × "n" efficacy score) + (3 × "n" efficacy score 3) + (4 × "n" efficacy score 4)]/total of actions was used to calculate terminal actions (i.e., serve, attack, and block).
- Efficiency was calculated using Coleman's equations (12) for attacks and counterattacks separately [Efficiency = (Points − errors) × 100/Attack attempts].

In addition, the number of points in a particular game phase, performance coefficients, and efficiency were classified into "low," "medium," and "high" performance categories using two-step cluster analysis [distance measure: log-likelihood; clustering criterion: Bayesian information criterion]. The category with the lowest frequency (≥10) was added to the category closest to it.

2.4 Procedure and reliability

The camera was positioned by the American AVP on an elevated plane with a full-court view to record the matches.

Lince® v.1.3 software was utilized for notational analysis (13). The software enabled the input of all categories using the observation tool and the simultaneous visualization of multiple videos within a single window. In addition, it allowed for pausing, rewinding, and reviewing the recorded notations. For further analysis, the notations were exported in a format supported by Microsoft Excel 2016.

The video observation process was conducted by three researchers, each with at least 5 years of experience in beach volleyball. Before data collection, the most experienced researcher led a training phase based on the procedures adopted by Amatria-Jiménez (14). A document outlining the observation criteria for each type of beach volleyball action was provided to the other researchers. Moreover, these criteria were presented in a lecture format, during which potential discrepancies were discussed. Practical training then followed, focusing on the application of the criteria using the Lince software. During this phase, the observers were instructed to watch an action, pause the video, make a notation, and proceed to the next action. They were allowed to rewind the video to re-watch actions when necessary. Moreover, the analyses were conducted independently, without any communication between the researchers' observations.

Following the training process, intra- and inter-observer reliability were assessed. To this end, the same eight sets (∼10% of the total number of sets) were analyzed twice by all observers, with a 20-day interval between assessments (15). A Kappa coefficient (K) ≥0.83 for all variables indicated good intra- and inter-observer reliability (16). In addition, to analyze the set of games, the following procedures were adopted: (a) an observer only began analyzing a match after having fully completed the observation of the previous one; (b) all sets of a given game were analyzed by the same observer.

2.5 Data analysis

The assumption of normal distribution was supported for all variables, following the recommendations proposed by George and Mallery (17), which consider skewness and kurtosis values between −2 and +2 as acceptable indicators of normality (Supplementary File 1). The data were shown as mean and standard deviation (SD). Moreover, two-way analysis of variance (ANOVA) (between-groups: set outcome, set score difference, and interactions) was used to compare dependent variables (points per game phase, coefficient of performance, and efficiency), and the Bonferroni *post-hoc test* was used for pairwise comparisons. Concerning effect size, the partial eta squared and magnitude were interpreted as follows: small: 0.01; moderate: 0.09; large: 0.25. Moreover, Cohen's "*d*" was used in pairwise comparisons and interpreted as per Hopkins et al.'s (18) recommendation: 0–0.2 (trivial), >0.2–0.6 (small), >0.6–1.2 (moderate), >1.2–2 (large), >2.0–4.0 (very large), and >4 (nearly perfect).

Moreover, binomial univariate and multivariate logistic regressions were performed to verify the relationship between the dependent variable [set result (winner or loser)] and independent variables (performance indicators). The multivariate logistic regression used a forward stepwise method to input variables into the model. Finally, the quality of the model was evaluated using the Hosmer–Lemeshow test, variance inflation factor (VIF), tolerance, and pseudo-R-squared values (r^2). All statistics were calculated using IBM SPSS Statistics for Windows, Version 20.0 (IBM Corp., Armonk, NY, USA), adopting an alpha value of ≤0.05.

3 Result

3.1 Points scored in the game phases

The number of points scored in K0, K2, and ∑(K2 + K3A + K3B) showed an interaction effect (Table 1). Thus, there was a significant difference between the winner and loser in points scored in K0 when the set was "easy" or "medium," and there was a difference between the winner and loser in points scored in K2 and ∑(K2 + K3A + K3B) for all set difficulties. Overall, the winner had an advantage for these performance indicators. Moreover, an outcome effect was observed in K3B [Winner = 1.03 ± 0.156 vs. Loser = 0.264 ± 0.143; $F_{(1.00,\ 152.00)}$ = 21.465; $p \leq 0.001$; $\eta_\rho^2 = 0.124$]. Concerning effect size in pairwise analysis, K2 was the best performance indicator for a "LD" set score difference; K0, K2, and $\sum \text{points}^{(K2\ +\ K3A\ +\ K3B)}$ were the best performance indicators for a "MD" set score difference; and K2 and $\sum \text{points}^{(K2\ +\ K3A\ +\ K3B)}$ were the best performance indicators for a "SD" set score difference (Figure 1).

3.2 Performance coefficients

The serve, serve reception, set, and attack performance coefficients showed an interaction effect (Table 2). Thus, serve and serve reception showed a significant difference for the "LD" and "MD" set score differences, set only showed a significant difference for the "MD" set score difference, and attack showed a significant difference for all set score differences. Moreover, an outcome effect was observed for block [Winner = 1.81 ± 0.70 vs. Loser = 1.32 ± 0.84; $F_{(1.00,\ 152.00)}$ = 17.094; $p \leq 0.001$; $\eta_\rho^2 = 0.102$], dig [Winner 2.07 ± 0.08 vs. 0.40 ± 0.09; $F_{(1.00,\ 152.00)}$ = 21.230; $p \leq 0.001$; $\eta_\rho^2 = 0.123$, set (counterattack) [Winner = 2.03 ± 0.40 vs. Loser = 1.73 ± 0.45; $F_{(1.00,\ 152.00)}$ = 21.230; $p \leq 0.001$; $\eta_\rho^2 = 0.123$], and attack (counterattack) [Winner = 2.77 ± 0.54 vs. Loser = 2.42 ± 0.80; $F_{(1.00,\ 152.00)}$ = 12.389; $p = 0.001$; $\eta_\rho^2 = 0.072$]. Regarding effect size, the pairwise analysis showed that attack was the best performance indicator in sets with the "LD" set score difference, with set and attack the best for the "MD" set score difference, and attack, block, and dig the best for the "SD" set score difference (Figure 2).

3.3 Efficiency

The attack efficiency showed an interaction effect (Table 2). Thus, the attack efficiency had a significant difference for all set score differences. Moreover, an outcome effect was observed for attack (counterattack) efficiency [Winner: 45.16 ± 22.18 vs. Loser: 29.09 ± 32.43; $F_{(2-152)}$ = 14.991; $p \leq 0.001$; $\eta_\rho^2 = 0.090$]. Concerning effect size, the pairwise analysis showed that attack efficiency had the largest effect size (Figure 3).

3.4 Univariate and multivariate logistic regression between the set outcome and performance indicators

The categorized performance indicators were used in the logistic regression (Table 3). For the attack and attack (counterattack) performance coefficients, the "medium" and "high" categories were combined for the analysis due to the low frequency of the "high" classification.

In the univariate analyses, a significant relationship was observed between set outcome and K0, K2, K3B, and $\sum \text{points}^{(K2\ +\ K3A\ +\ K3B)}$; the serve, serve reception, set, attack,

TABLE 1 Comparison of points scored in different game phases stratified by set outcome and set score difference.

Game phase	Winner						Loser						Two-way ANOVA (Interaction)
	LD (n = 9)		MD (n = 25)		SD (n = 45)		LD (n = 9)		MD (n = 25)		SD (n = 45)		
	Mean	SD (±)	Mean	SD (±)	Mean	SD (±)	Mean	SD (±)	Mean	SD (±)	Mean	SD (±)	
K0	1.22[a]	0.83	1.72[a]	1.24	0.98	1.01	0.22	0.44	0.36	0.57	0.89	1.11	$F_{(2.0,\ 152.0)}$ = 6.939; $p < 0.001$; η_ρ^2 = 0.084*
K1	4.78	1.72	7.24	2.13	8.27	1.95	5.00	1.41	6.16	1.82	8.00	1.85	$F_{(2.0,\ 152.0)}$ = 1.080; p = 0.342; η_ρ^2= 0.014
K2	5.22[a]	2.28	4.28[a]	2.13	3.40[a]	1.63	0.44	0.73	1.32	1.03	1.93	1.12	$F_{(2.0,\ 152.0)}$ = 10.516; $p < 0.001$; η_ρ^2 = 0.122*
K3A	1.11	0.93	1.72	1.21	1.62	1.09	1.11	0.78	1.36	0.99	1.93	1.36	$F_{(2.0,\ 152.0)}$ = 1.356; p = 0.261; η_ρ^2 = 0.018
K3B[b]	1.11	1.05	1.08	1.26	0.91	0.95	0.11	0.33	0.28	0.46	0.40	0.62	$F_{(2.0,\ 152.0)}$ = 0.880; p = 0.417; η_ρ^2 = 0.011
$\sum^{(K2\ +\ K3A\ +\ K3B)}$	7.44[a]	3.09	7.08[a]	2.60	5.93[a]	2.08	2.96	1.67	4.27	1.91	3.56	1.96	$F_{(2.0,\ 152.0)}$ = 10.302; $p < 0.001$; η_ρ^2 = 0.119*

SD, standard deviation; η_ρ^2, partial eta squared; LD, large difference; MD, medium difference; SD, short difference.
[a]Statistically significant difference ($p \leq 0.05$) between the winning and losing teams in terms of the set score difference (LD, MD, SD).
[b]Statistically significant difference ($p \leq 0.05$) between the winner vs. loser teams.
*$p \leq 0.05$.

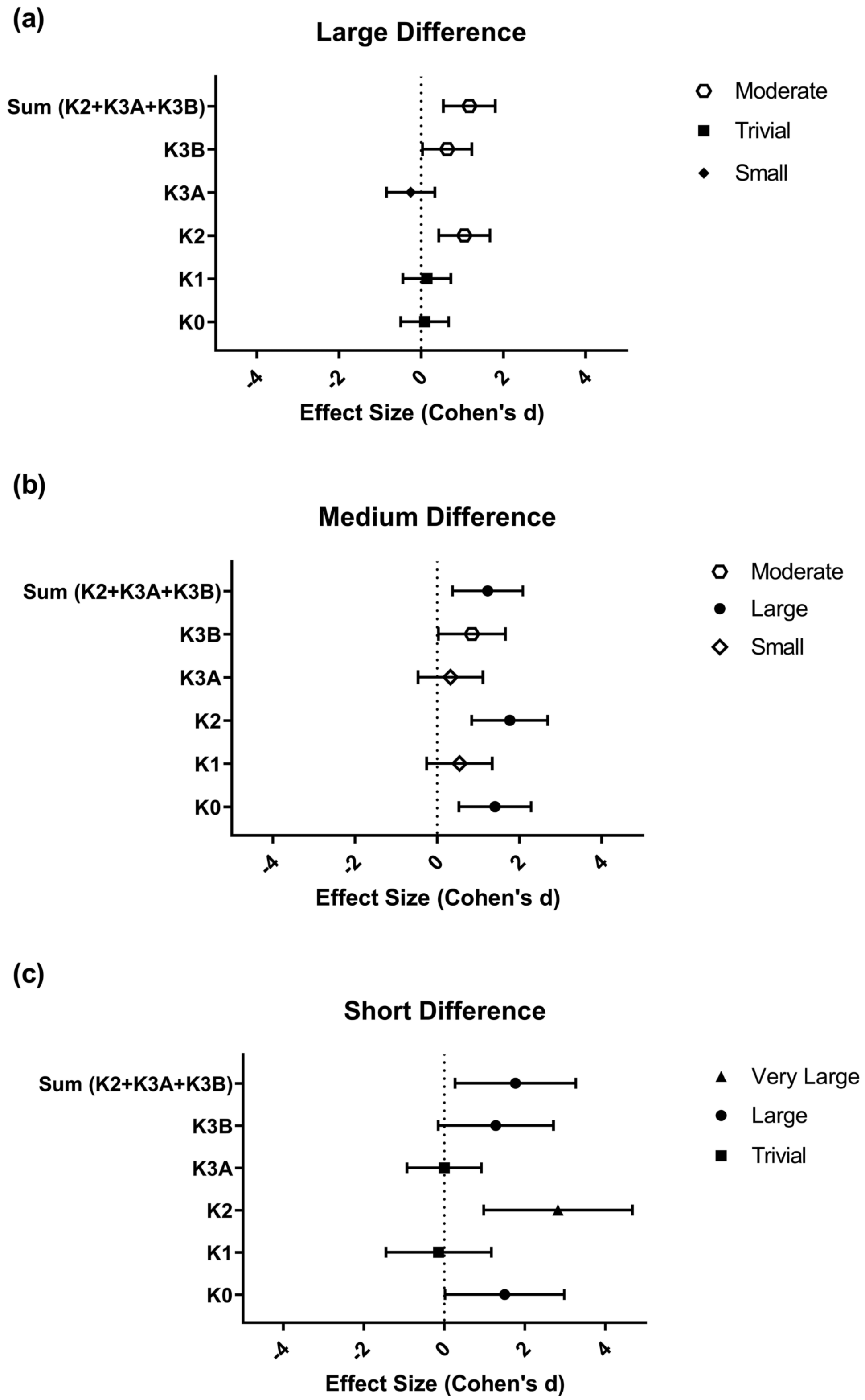

FIGURE 1
Effect sizes for the differences in points scored across game phases, stratified by set outcome and set score difference. **(a)** Large set score difference; **(b)** medium set score difference; **(c)** short set score difference. Note: A value of $d > 0$ indicates an effect in favor of the winner, while $d < 0$ indicates an effect in favor of the loser. The symbols on the right indicate the magnitude of the effect.

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TABLE 2 Comparison of performance coefficients and efficiency stratified by set outcome and set score difference.

Performance indicators	Winner						Loser						Two-way ANOVA$^{(Interaction)}$
	LD (n = 9)		MD (n = 25)		SD (n = 45)		LD (n = 9)		MD (n = 25)		SD (n = 45)		
	Mean	SD(±)	Mean	SD(±)	Mean	SD(±)	Mean	SD(±)	Mean	SD(±)	Mean	SD(±)	
PC serve	1.81[a]	0.21	1.64[a]	0.39	1.47	0.35	1.27	0.35	1.32	0.39	1.39	0.37	$F_{(2.00,\ 152.00)} = 3.798$; $p = 0.025$; $\eta_p^2 = 0.048$
PC serve reception	2.48[a]	0.37	2.43[a]	0.38	2.35	0.35	2.09	0.20	2.15	0.30	2.32	0.31	$F_{(2.00,\ 152.00)} = 3.533$; $p = 0.032$; $\eta_p^2 = 0.044$
PC set	2.68	0.39	2.81[a]	0.27	2.78	0.31	2.56	0.40	2.39	0.37	2.65	0.35	$F_{(2.00,\ 152.00)} = 3.293$; $p = 0.040$; $\eta_p^2 = 0.042$
PC attack	3.09[a]	0.55	2.97[a]	0.43	2.84[a]	0.41	1.96	0.17	2.26	0.40	2.60	0.42	$F_{(2.00,\ 152.00)} = 10.975$; $p < 0.001$; $\eta_p^2 = 0.126$
PC block[b]	1.94	0.75	1.84	0.71	1.77	0.70	0.83	0.78	1.33	0.92	1.33	0.92	$F_{(2.00,\ 151.00)} = 2.361$; $p = 0.098$; $\eta_p^2 = 0.030$
PC dig[b]	2.16	0.36	2.06	0.49	1.98	0.35	1.53	0.55	1.74	0.37	1.76	0.48	$F_{(2.00,\ 152.00)} = 1.723$; $p = 0.182$; $\eta_p^2 = 0.022$
PC set (CT)[b]	2.25	0.26	2.48	0.43	2.37	0.36	1.89	0.70	2.31	0.48	2.32	0.41	$F_{(2.00,\ 152.00)} = 1.070$; $p = 0.346$; $\eta_p^2 = 0.014$
PC attack (CT)[b]	2.86	0.45	2.88	0.46	2.69	0.60	2.15	0.94	2.32	0.95	2.53	0.69	$F_{(2.00,\ 152.00)} = 2.071$; $p = 0.130$; $\eta_p^2 = 0.027$
EFF attack	49.81[a]	19.30	53.18[a]	18.32	45.19	18.89	04.80	14.50	21.77	15.23	32.89	14.92	$F_{(2.00,\ 152.00)} = 9.730$; $p < 0.001$; $\eta_p^2 = 0.113$*
EFF attack (CA)[b]	53.06	16.20	50.20	21.58	40.78	22.88	21.98	33.90	26.98	37.78	31.69	29.27	$F_{(2.00,\ 152.00)} = 1.780$; $p = 0.172$; $\eta_p^2 = 0.023$

PC, performance coefficient; EFF, efficiency; CA, counterattack; SD, standard deviation; η_p^2, partial eta squared; LD, large difference; MD, medium difference; SD, short difference.
[a]Statistically significant difference ($p \leq 0.05$) between the winning and losing teams in terms of the set score difference (LD, MD, SD).
[b]Statistically significant difference ($p \leq 0.05$) between the winner vs. loser teams.
*$p \leq 0.05$.

block, dig, and counterattack performance coefficients; and attack and counterattack efficiencies (more details can be found in Supplementary File 2). K2 and $\sum$points$^{(K2 + K3A + K3B)}$ had the highest r^2 values (0.46 and 0.44, respectively).

In the multivariate analysis, Model 1 included the serve, serve reception, set, attack, block, dig, and counterattack performance coefficients, and the attack and counterattack efficiencies. A significant relationship was observed between set outcome and the serve, set, block, and dig performance coefficients, and the attack and counterattack efficiencies, regardless of the performance classification (Table 4). Moreover, "high" counterattack efficiency, "high" attack efficiency, and "high" block and dig performance coefficients were the best performance indicators, increasing the probability of winning the set by 26.207, 18.490, 15.033, and 13.811 times, respectively, compared to the "low" performance classification. Regarding model quality, there was no multicollinearity [VIFmean = 1.07 (±0.06); tolerance: 0.93 (±0.05)], the expected frequencies were not different from those observed (Hosmer–Lemeshow test: $p = 0.684$), 60% of the variability in set outcome was explained by the model, and the accuracy of the predictions was 82.91%.

In Model 2, the points scored in the game phases variable was added. A significant relationship was observed between the set outcome and points scored in K0, K2, and K3B, and the set performance coefficient was classified as "high" (Table 5). Moreover, a significant trend was observed for the "medium + high" attack performance coefficient ($p = 0.058$). It is noteworthy that "high" performances in K2 and K3B were the main performance indicators, increasing the likelihood of winning the set by 604.90 and 181.37 times, respectively, compared to a "low" performance. In relation to model quality, there was no multicollinearity [VIF^{mean} = 1.54 (±0.06); tolerance: 0.73 (±0.27)], the expected frequencies were not different from those observed (Hosmer–Lemeshow test: $p = 0.735$), 78% of the variability in set outcome was explained by the model, and the accuracy of the predictions was 90.50%.

4 Discussion

The purpose of this study was to analyze technical-tactical performance indicators in terms of the set outcome, set score difference, and game phase. The winners scored the most points in all game phases, had a higher performance coefficients and efficiency than the losers, independent of the set score difference. However, the set score difference seemed to influence the difference between the winner and the loser. Thus, a significant difference in points scored in game phases was observed for points scored in K0 for the "LD" and "MD" set score differences, and for points scored in K2 and $\sum$points$^{(K2 + K2+\ K3B)}$ for set score difference overall. Furthermore, the winners had better serve, serve reception, and attack performance coefficients in sets with an "LD" set score difference; serve reception and attack performance coefficients in sets with an "MD" set score difference; and attack performance coefficient in sets with an

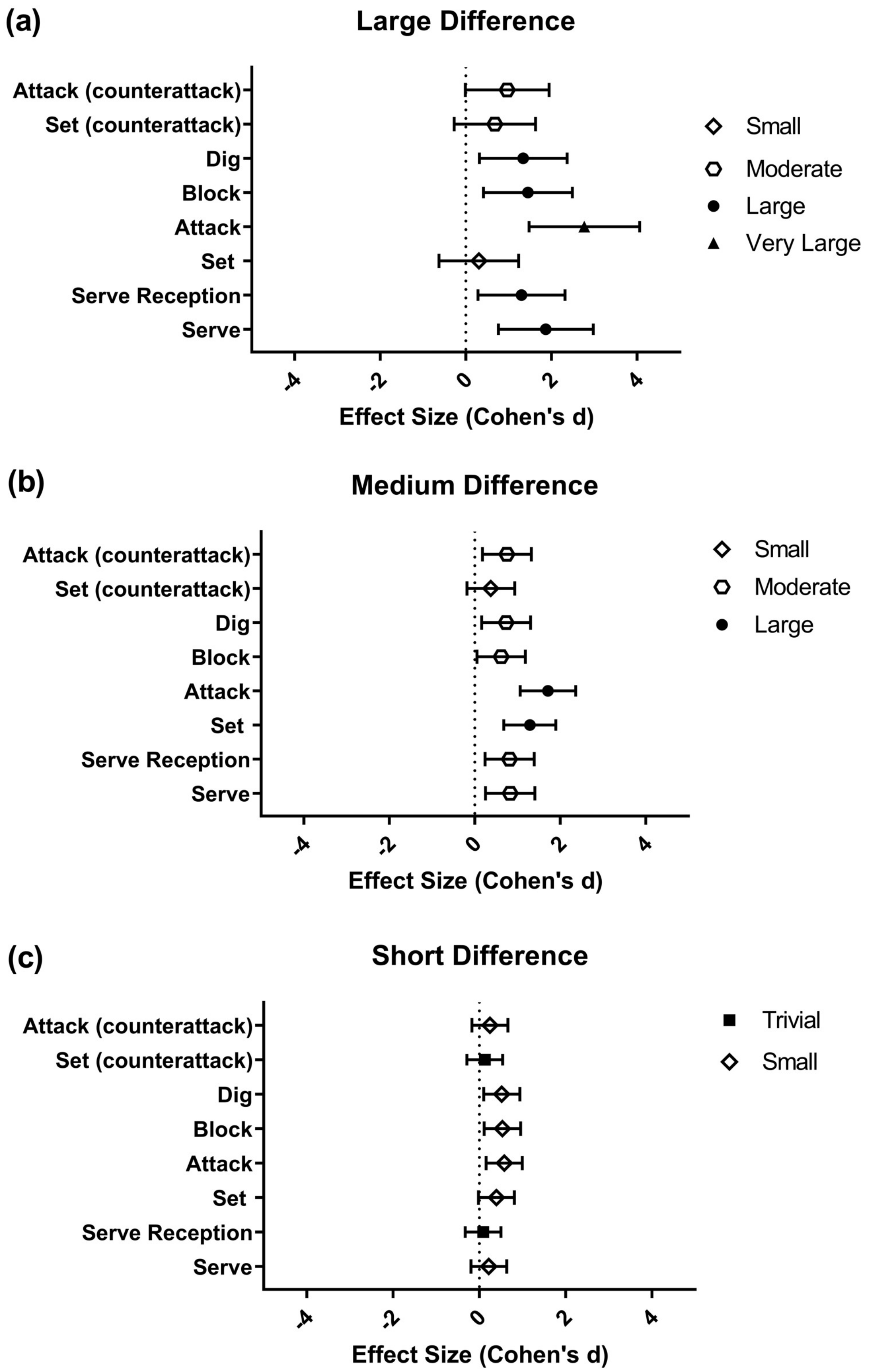

FIGURE 2
Effect sizes for the differences in performance indicators between winners and losers across different set score differences. (a) Large set score difference; (b) medium set score difference; (c) short set score difference. Note: A value of $d > 0$ indicates an effect in favor of the winner, while $d < 0$ indicates an effect in favor of the loser. The symbols on the right represent the magnitude of the effect.

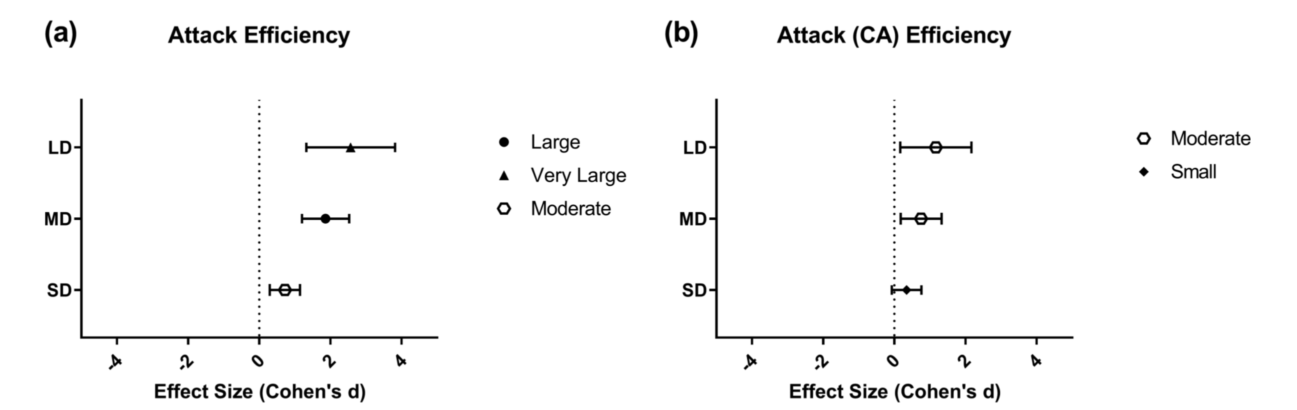

FIGURE 3
Effect sizes for the differences in attack efficiency (a) and counterattack efficiency (b) between winners and losers across different set score differences. Note: LD, large difference; MD, medium difference; SD, short difference. A value of $d > 0$ indicates an effect in favor of the winner, while $d < 0$ indicates an effect in favor of the loser. The symbols on the right indicate the magnitude of the effect.

TABLE 3 Performance indicator categories.

Performance indicator	Performance categories		
	Low	Medium	High
K0	0	1	≥2
K1	≤5	6–7	≥8
K2	≤1	2–3	≥4
K3A	≤1	2	≥3
K3B	0	1	≥2
∑(K2 + K3A + K3B)	≤3	4–6	≥7
PC serve	≤1.40	1.41–1.80	≥1.85
PC server reception	≤2.21	2.23–2.70	≥2.75
PC set	≤2.26	2.31–2.76	≥2.77
PC attack	≤2.56	2.63–3.25	≥3.27
PC block	≤1.33	1.40–2.22	≥2.40
PC dig	≤1.63	1.66–2.42	≥2.66
PC set (CA)	≤2.30	2.33–2.77	≥2.80
PC attack (CA)	≤2.40	2.42–3.30	≥3.40
EFF attack	≤18.18	18.75–46.15	≥46.66
EFF counterattack	≤0.00	10.00–44.40	≥45.50

PC, performance coefficient; EFF, efficiency; CA, counterattack.
Categorized by distance measure: log-likelihood; clustering criterion: Bayesian information criterion method.

TABLE 4 Logistic regression between the set outcome and performance indicators—Model 1.

Set outcome[a]	β	SE	Odds ratio	Sig.
Performance indicator[b]				
PC serve	—	—	—	0.007*
Medium	1.822	0.651	6.186	0.005*
High	1.159	0.574	3.186	0.044
PC set	—	—	—	0.043*
Medium	0.236	0.805	1.267	0.769
High	1.408	0.700	4.088	0.044*
PC block	—	—	—	0.003*
Medium	0.840	0.515	2.316	0.103
High	2.710	0.804	15.033	<0.001*
PC dig	—	—	—	0.006*
Medium	1.646	0.565	5.187	0.004*
High	2.625	1.046	13.811	0.012*
EFF attack	—	—	—	<0.001*
Medium	1.216	0.717	3.375	0.090
High	3.266	0.810	26.207	<0.001*
EFF counterattack	—	—	—	<0.001*
Medium	1.721	0.744	5.590	0.021*
High	2.917	0.809	18.490	<0.001*

PC, performance coefficient; EFF, efficiency; CA, counterattack.
Hosmer–Lemeshow test: $p = 0.684$; $r^2 = 0.605$; $VIF^{mean} = 1.07$ (±0.06); tolerance: 0.93 (±0.05); model's accuracy = 82.91%.
[a]Winner was used as the reference category.
[b]Low was used as the reference category.
*$p \leq 0.05$.

"SD" set score difference than the losers. Additionally, winners showed superior performance coefficients in blocking, setting (counterattack), and attack efficiency (counterattack), independently of set score difference. Regarding the magnitude of differences, both the effect sizes and the number of key performance indicators distinguishing winners from losers tended to decrease as the set score difference decreased, suggesting that, in closely contested sets, fewer indicators determine the outcome. Moreover, the logistic regression analyses showed a positive relationship between winning a set and attack efficiency, attack (counterattack) efficiency, dig and block performance coefficients (see Model 1), and points scored in K2 and K3B (see Model 2). In general terms, the data seem to confirm the initial hypotheses.

The serve is a player's first opportunity to score points in a rally or at least impair the organization of their opponent's attack. Previously, Medeiros et al. (6) observed that the winning male teams scored more points than the losers with their serve, which corroborates our data. However, the aim of the serve reception phase is to control the ball to organize an effective attack. In sets with "easy" and "medium" difficulties, points in K0 and the serve and serve reception performance coefficients seem to differentiate winners and losers, but this did not happen in "hard" sets. Thus, in easier sets, the winning team was able to serve more effectively and neutralize the opponent's serve through a strong serve-reception performance. Moreover, high-quality reception

TABLE 5 Logistic regression between the set outcome and performance indicators—Model 2.

Set outcome[a]	β	SE	Odds ratio	Sig.
Performance indicator[b]				
K0	—	—	—	0.039*
Medium	1.205	0.724	3.336	0.096
High	1.932	0.774	6.907	0.013*
K2	—	—	—	<0.001
Medium	1.328	0.763	3.772	0.082
High	6.405	1.363	604.904	<0.001*
K3B	—	—	—	<0.001*
Medium	1.149	0.682	3.155	0.092
High	5.201	1.240	181.371	0.000*
PC Set	—	—	—	0.061
Medium	1.366	1.152	3.919	0.236
High	2.377	1.084	10.771	0.028*
PC attack (medium + high)	2.256	1.188	9.544	0.058
EFF attack	—	—	—	0.016*
Medium	−0.968	1.172	0.380	0.409
High	1.195	1.410	3.304	0.397
Constant	−7.188	1.648	0.001	<0.001

PC, performance coefficient; EFF, efficiency.
Hosmer–Lemeshow test: $p = 0.735$; $r^2 = 0.789$; $\text{VIF}^{\text{mean}} = 1.54\ (\pm 0.65)$; tolerance: 0.73 (±0.27); model's accuracy = 90.50%.
[a]Winner was used as the reference category.
[b]Low was used as the reference category.
*$p \le 0.05$.

facilitates setting and allows the player to apply the appropriate technique according to the tactical demands (8).

In this sense, although the number of points scored in K0 was ∼2–3 points per set, which is a small contribution to scoring 21 points to win the set, and serve reception and setting are actions that do not score points, these actions interfere with or are fundamental support for an attack. Our data showed that attack performance (K1) is important for victory since the attack performance coefficient and efficiency differentiated the outcome and/or were associated with winning a set, as an attack not only allows a player to score a point but also harms the opponent's counterattack. In a previous study, Medeiros et al. (6) found in a study on male players of various levels that points scored in K1 had a small effect on winning the set, but the performance coefficient and errors seemed to have a moderate to large effect. In women, this effect appears to be similar; however, we found that in sets with a "LD" set score difference, the attack performance coefficient and efficiency determined the winner. In other words, it is unlikely that a team will win a set without a superior performance in K1. Moreover, using absolute point scores should be avoided when evaluating athletes' performance in this game phase.

Concerning the counterattack phases (K2, K3A, and K3B), points scored in K2 and K3B seem to be the main performance indicators in high-level women's beach volleyball. The effect of $\sum \text{points}^{(\text{K2 + K3A + K3B})}$ on the outcome was probably leveraged by the performance in K2 and K3B; thus, this performance indicator does not present additional advantages in match analysis. Our data partially corroborate what was previously observed in male athletes (6), as although K2 was an important indicator of victory, K3B was favorable to losers. These data suggest that the adoption of parameters related to technical-tactical performance should be interpreted according to gender. Although some performance indicators are common to both men and women, there may be some differences. When analyzing the counterattack actions specifically, a block, a dig, and an attack (counterattack) were the main indicators of victory. However, blocking and defending operate similarly to serve and serve reception. The importance of these actions is not based on the points obtained, but on creating opportunities for a counterattack. Previously, it was identified that winners are superior in points scored by blocking (9); however, this results in a limited number of points (i.e., 1–2 per set), reinforcing the idea of blocking being a secondary indicator of victory in a set.

In general, this data can be used as a benchmark for the performance of athletes competing at a high level. Based on the knowledge of the factors that lead to winning a set in women's high-performance beach volleyball, some strategies can be adopted in training and competitions. Concerning one's serve, using either a power jump or floating jump serve and aiming for the central and line zones seems to improve performance (19). Furthermore, the speed of the ball has been found to be related to scoring a point (20); however, the players and coaches must keep in mind that serving at a very high speed increases the chances of error (20). Therefore, an effective serving strategy to score points is to direct the ball between opposing players or toward the boundary lines at a speed of at least 12–16 m s^{-1} (19, 20). Moreover, these strategies can impair the serve reception, increase the performance coefficient, help a player score a point in another game phase, and consequently increase the chance of winning the set.

Concerning serve reception, training should provide opportunities for players to receive float serves or jump float serves because they are the types predominantly used by female players (21). In addition, serve reception and setting can be trained together because they naturally occur in sequence in a game, and this will allow players to adapt to their teammate's serve-reception behavior. Regarding blocking and digging, these actions are strongly related, and strategies are usually adopted before the attack action. However, parsing visual information and decision-making are fundamental (22). Therefore, these aspects need to be present in training. Moreover, the failure of an attack during K1 usually leads a player to modify their subsequent attack [i.e., shot or smash (23)] and athletes need to be aware of this. Finally, during attacking actions, female players perform shots and smashes with similar frequency (21). Therefore, training should not focus solely on the execution of the attacking action but also emphasize the importance of perceiving the opponent's positioning. This ensures that even technically perfect attacks are not executed out of context of the tactical demands of the match.

Regarding the presentation of data to players, it is recommended that the following performance indicators be employed: the efficiency of the attack and counterattack; the dig and block performance coefficients; and points scored in K2 and K3B. These metrics are fundamental for winning a set and avoiding redundancy of information, in line with the idea of key performance indicators (24). Finally, some limitations of this study need to be acknowledged. The match analyses were from two AVP Gold Series events, which bring together the best athletes in the AVP rankings. Therefore, this data should be extrapolated with caution to grassroots and lower-level athletes. In addition, the stages of the competition (i.e., group stage, semi-finals, etc.) were not taken into account; in future studies, this could be included as a moderating factor. Another important point is that we did not consider the moments of the match (i.e., start of the game, set points, etc.), which may in the future provide important insights into the crucial moment of victory. Finally, future studies could consider incorporating qualitative inferential analysis approaches (e.g., polar coordinate analysis) to enhance the understanding of performance indicators in beach volleyball.

5 Conclusion

In conclusion, attack efficiency was an important performance indicator. However, it is important to highlight that the main indicators of performance were derived from the points scored and actions performed during the counterattack phases, especially K2 and K3B. In addition, the set score difference reflects the balance of the set (i.e., the smaller the score difference, the smaller the difference in performance indicators between the winner and the loser of the set). Therefore, these parameters can be used to guide training programs (e.g., increased training volume focusing on a dig during a counterattack) and evaluate team performance (e.g., superiority over the opponent).

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

This study involving humans was approved by the Ethics and Research Committee of the Health Sciences Center of the Federal University of Paraíba. The study was conducted in accordance with the local legislation and institutional requirements. Written informed consent for participation was not required from the participants or the participants' legal guardians/next of kin because this study involved game analysis using videos made freely available in open access.

Author contributions

YPdC: Conceptualization, Data curation, Writing – original draft, Writing – review & editing. FSM: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – review & editing. LRR: Data curation, Investigation, Writing – review & editing. AGdA: Writing – review & editing. GRB: Conceptualization, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fspor.2025.1584173/full#supplementary-material

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